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The Limits of Lending: Banks and Technology Adoption Across Russia*

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Abstract

We exploit historical and contemporaneous variation in local credit markets across Russia to identify the impact of credit constraints on firm-level innovation. We find that access to bank credit helps firms to adopt existing products and production processes that are new to them. They introduce these technologies either with the help of suppliers and clients or by acquiring external know-how. We find no evidence that bank credit also stimulates firm innovation through in-house R&D. This suggests that banks can facilitate the diffusion of technologies within developing countries but that their role in pushing the technological frontier is limited.

Keywords: Credit constraints; firm innovation; technological change

JEL Codes: D22, F63, G21, O12, O31

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1 Introduction

Firm innovation is an important driver of factor productivity and long-term economic growth (Romer, 1990; Aghion and Howitt, 1992). In countries close to the technological frontier, innovation typically entails research and development (R&D) and the invention of new products and technologies. In less advanced economies, innovation mostly involves imitation as firms adopt existing products and processes and adapt them to local circumstances (Grossman and Helpman, 1991; Acemoglu, Aghion and Zilibotti, 2006). Such innovation helps countries to catch up to the technological frontier but does not push that frontier itself.

As firms adopt products and processes that were developed elsewhere, technologies spread across and within countries. The speed with which technologies spread varies greatly from country to country and can explain up to a quarter of total variation in national income levels (Comin and Hobijn, 2010). Despite this central role of technological diffusion in determining wealth outcomes, the mechanisms that underpin the spread of products and production processes remain poorly understood. This paper focuses on one such mechanism: the impact of credit constraints on technological adoption.

Funding constraints may limit the adoption of technology because external inventions, which are typically context-specific and involve tacit know-how, are costly to integrate into a firm's production structure. Estimates for the manufacturing sector suggest that imitation can even cost up to two-thirds of the costs of the original invention (Mansfield, Schwartz and Wagner, 1981). Firms may therefore need external resources to adapt technologies to local circumstances. If external financing is unavailable, firms may not be able to adopt and adapt state-of-the-art production technologies, thus limiting the diffusion of these technologies from rich to poor countries.

Exactly how—and how much—external finance helps firms to innovate, be it through in-house R&D or through the adoption of existing products and processes, remains a matter of debate. A key empirical problem hampering this discussion is the dearth of firm-level information on these two forms of innovation. This problem is compounded by the absence of convincing identification strategies to mitigate endogeneity concerns.

To shed more light on this issue, we bring new firm-level evidence to bear and analyze for a large sample of Russian firms to what extent credit constraints inhibit innovation. Russia is an interesting setting to explore this question, given that—as in other large emerging markets like India and China—firms continue to be plagued by credit constraints. At the same time, many firms perform poorly when it comes to adopting technology.[1] We investigate whether this second observation can be explained by the first.

We employ a rich dataset with information on the demand for and supply of bank credit in a regionally representative sample of 4,220 Russian firms. We know the geographical location of these firms and have detailed information on their innovation activities, including R&D and the adoption of new products, processes, and organizational structures. Another unique data feature is that we know *how* firms innovate, for instance whether they cooperate with suppliers or acquire existing technologies or patents. We also know whether the products and processes they introduce are only new to the firm itself or also to the local market or Russia as a whole. This allows us to demarcate the margins along which access to credit allows firms to innovate and to facilitate technological diffusion.

Our identification rests on merging these firm-level data with two detailed datasets on geographical variation in Russian credit markets. First, we use newly collected information on the location of over 45,000 bank branches across Russia. Second, we employ data on historical variation in the local presence of so-called spetsbanks. This variation reflects bureaucratic power struggles just before the collapse of the Soviet Union and is unrelated to economic conditions, past or present. We exploit this historical and contemporaneous variation in the spatial distribution of banks to explain differences in firms' ability to access credit and, in a second step, their innovation activity at the extensive and intensive margins. We also know the lender identity in case a firm borrows. Such matched bank-firm data have not yet been used in the innovation literature (Herrera and Minetti, 2007) and allow us to assess whether the type of lender impacts firm innovation over and above the effect of relaxed credit constraints.

To preview our results, we find that especially small and opaque firms are less credit constrained in local markets where for historical (and exogenous) reasons the number of bank branches per capita is higher, where branch ownership is more concentrated, and where foreign banks have a higher market share. We then show that less stringent credit constraints translate into more technology adoption at both the extensive and intensive margins but not into more R&D. This suggests that while bank credit does not allow firms to push the technological frontier itself, banks can play a crucial role in stimulating factor productivity in developing countries by enabling firms to upgrade their products and processes. Additional results indicate that foreign-owned banks

[1] According to the World Economic Forum's *Global Competitiveness Report (2013-2014)* Russia ranks 126$^{\text{th}}$ out of 148 countries in terms of firm-level technology absorption.

play a special role in this upgrading process. Not only is innovation activity higher in localities with more foreign banks, we also find that *conditional on borrowing* receiving credit from a foreign as opposed to a domestic bank further boosts firm innovation.

We subject these results to a battery of tests and conclude that our inferences are robust. We also provide three pieces of evidence in support of our identification strategy. First, we estimate locality-level regressions to analyze to what extent local business-sector characteristics explain local banking structures. We find that the composition of local credit markets is orthogonal to a large set of observable business characteristics. Second, *unobservables* could explain part of the correlation between local banking and firm innovation. We therefore quantify the relative importance of omitted variable bias by assessing the stability of our estimated parameters when adding covariates. This shows that unobserved heterogeneity is unlikely to explain much of the impact we document and that, if anything, we may somewhat underestimate the true causal effect. Third, an important assumption underlying our analysis is that local banking structures only affect firm innovation through the probability that firms are credit constrained. We analyze the sensitivity of our results to a relaxation of this strict exogeneity assumption and continue to find a strong impact of credit constraints on technological innovation.

We proceed as follows. Section 2 reviews the related literature after which Section 3 provides a primer on banking in Russia. Section 4 explains our data while Section 5 introduces the identification strategy and empirical methodology. Section 6 describes our main results after which Section 7 provides two extensions. Section 8 concludes.

2 Related literature

This paper builds on a well-established literature on the role of banks in economic development. This literature dates back to Adam Smith's assertion that the establishment of the first Scottish banks increased local trade and economic activity.[2] Recent empirical research has provided more rigorous evidence on the positive impact of financial intermediation on economic growth[3] while advances in endogenous growth theory have strengthened the theoretical underpinning of this relationship.[4] Especially relevant to this paper is the Schumpeterian model that Aghion, Howitt and Mayer-Foulkes (2005)

[2] "*That banks have contributed a good deal to this increase, cannot be doubted*" (1776, p. 394). Subsequent contributions include Schumpeter (1934), Gerschenkron (1962) and McKinnon (1973).

[3] See for instance La Porta, López-de-Silanes, Shleifer and Vishny (1997), Beck, Levine and Loayza (2000), and Demirgüç-Kunt and Levine (2001).

[4] See Greenwood and Jovanovic (1990) and King and Levine (1993).

use to show how financial constraints can prevent developing countries from exploiting R&D that was carried out in countries closer to the technological frontier.

More recently, economists have started to use microeconomic data to investigate the relationship between local banking markets and firm innovation—an important open research question (Chemmanur and Fulghieri, 2014). Nanda and Nicholas (2014) show that the severity of local banking distress during the Great Depression was negatively associated with the quantity and quality of firm patenting. Amore, Schneider and Žaldokas (2013) and Chava, Oettl, Subramanian and Subramanian (2013) find that inter-state banking deregulation in the U.S. during the 1970s and 1980s boosted firm innovation, as proxied by the number of patents. Two related papers use Italian data. Benfratello, Schiantarelli and Sembenelli (2008) show that a higher local branch density is associated with more firm innovation. Alessandrini, Presbitero and Zazzaro (2010) find that local lender concentration has a positive effect on innovation by small firms.

A related literature investigates the role of bank debt as a funding source for firm innovation. A first set of papers take a rather pessimistic view and stress the uncertain nature of innovation—particularly R&D. This may make banks less suitable financiers for at least four reasons. First, the assets associated with innovation are often intangible, firm-specific and linked to human capital (Hall and Lerner, 2010). They are therefore difficult to redeploy elsewhere and thus difficult for banks to collateralize (Carpenter and Petersen, 2002). Second, innovative firms typically generate volatile cash flows, at least initially (Brown, Martinsson and Petersen, 2012). Third, banks may simply lack the skills needed to assess technologies at the early stages of adoption (Ueda, 2004). Lastly, 'technologically conservative' banks may fear that funding new technologies will erode the value of collateral underlying existing loans—which will mostly represent old technologies (Minetti, 2011). For all of these reasons, banks may be either unwilling or unable to fund innovative firms. Hsu, Tian and Xu (2014) provide cross-country evidence that industries that depend on external finance and are high-tech intensive are less likely to file patents in countries with better developed credit markets.

Other contributions are more optimistic and stress banks' ability to overcome agency problems by building relationships with borrowers (Rajan and Zingales, 2001). Banking, and in particular relationship lending, may overcome information asymmetries related to innovative firms that cannot be overcome in public debt markets. De la Fuente and Marin (1996) show in an endogenous growth model how bank monitoring reduces moral hazard among entrepreneurs, thus stimulating the development of new product types.

Empirically, Herrera and Minetti (2007) show that longer bank-firm relationships are associated with more firm innovation in Italy. Ayyagari, Demirguc-Kunt and Maksimovic (2011) investigate the correlation between the use of bank credit and innovation in a firm-level dataset across 47 developing countries. They find that the use of external finance is related to more firm innovation.[5] Gorodnichenko and Schnitzer (2013) use survey data to show that self-reported credit constraints partly explain cross-firm variation in innovation activity.

Our contribution is twofold. First, we trace the chain from local banking structures to firms' access to credit and their subsequent propensity to innovate. Whereas previous papers provided evidence on parts of this chain, we combine these elements in an integrated empirical framework. We also exploit information on the type of lender.

Second, our newly collected data allow us to exploit firm-level information on a large number of innovation outcomes—not just R&D and patenting. This allows for a rich analysis of the margins along which access to credit can (and cannot) impact firm innovation. Measures of technological change are typically unavailable at the micro level and it is the use of such detailed innovation measures that allows us to provide firm-level evidence in support of one of the main predictions of Aghion, Howitt and Mayer-Foulkes (2005), namely that financial constraints can impede the absorption of foreign technologies in developing countries.

3 A short history of Russian banking

The Soviet Union ceased to exist on Christmas Day, 1991 and the Russian Federation was established the next day. During much of the preceding 70 years, Soviet banking had been organized in the form of a single monobank, Gosbank, that provided state-owned firms with loans so they could meet centrally-planned production targets. Perhaps somewhat surprisingly, socialist leaders attached great importance to the presence of bank branches across the vast Russian territory. Lenin wrote in the lead up to the October Revolution that:

> "*Without big banks socialism would be impossible.* The big banks *are* the 'state apparatus' which we *need* to bring about socialism. A single State Bank, the biggest of the big, with branches in every rural district [...] will

[5] The authors do not address endogeneity concerns and take the actual use of external funding as a proxy for (the absence of) credit constraints. This is an imperfect measure as firms without a bank loan may either not need one or need one but be credit constrained.

> constitute as much as nine-tenths of the socialist apparatus [Italics in the original, Lenin (1917)]."

Just before the Soviet Union collapsed, Soviet bureaucrats decided to reorganize the vast banking network that spans Russia's territory.[6] As part of Mikhail Gorbachev's perestroika program, the Gosbank was split into a central bank and five 'spetsbanks': specialized banks to serve specific segments of the economy. Two of these, the savings bank (Sberbank) and the foreign-trade bank (Vneshtorgbank) remained under Gosbank control. Three others became separate entities to lend to agricultural enterprises (Agromprombank), projects in housing and social development (Zhilsotsbank), and the general industry and construction sectors (Promstroibank).

Starting in September 1990, many branches of these spetsbanks were 'spontaneously privatized' as branch managers were offered the opportunity to turn their branch into an independent joint-stock bank. The sudden and erratic privatization of spetsbanks only took a few months and was completed by the end of 1990. For our purposes, two features of this sudden decentralization process are particularly important. First, the process was not part of any planned economic transition program. Central authorities exercised little control over the rapid and unexpected decentralization and there was no market-oriented legal framework to guide it. Berkowitz, Hoekstra and Schoors (2014, p.6) describe how the process was conducted by "Soviet administrators on the basis of their own preferences" which were "divorced from forces shaping organizations in market economies." The resulting geographical distribution of bank branches across Russia's territory therefore reflected idiosyncratic and bureaucratic forces rather than economic fundamentals.

Second, the sudden privatization of spetsbanks *before* the collapse of the Soviet Union also shaped the entry and location of *new* commercial banks soon *after* the Union ceased to exist. Johnson (2000) describes how spetsbank managers benefited from transferring resources that they received through the state system into newly established commercial banks. It was attractive for managers to set up new banks near existing spetsbanks to facilitate the move of state resources into private hands. As a result, the initial geographical branching structure from before the Soviet breakdown became even more cemented into Russia's new commercial banking system. The historical persistence in exogenous variation in local branch density, which resulted from arbitrary bureaucratic decisions just before the Soviet Union collapsed, is a crucial feature of the

[6] This section draws on Johnson (2000), Schoors (2003), and Schoors and Yudaeva (2013).

Russian banking landscape and one that we exploit in our empirical analysis.

Once a new banking landscape was established in the early 1990s, years of high inflation meant that Russian banks—both (former) spetsbanks and new commercial banks—mainly invested in short-term government bonds rather than lend to firms. This phase came to a halt in 1998 when the Russian government defaulted, the ruble devalued, and many banks went bankrupt. Banks increasingly started to operate as financial intermediaries after the 1998 financial crisis, when the state reduced its funding needs. Households and corporations rapidly expanded their borrowing against the background of an improving macroeconomic environment, higher income levels, and institutional reforms. In December 2003 a comprehensive deposit insurance scheme was introduced, which not only led to a rapid increase in household deposits but also to the revocation of numerous banking licenses.

Today, the Russian financial system remains bank dominated as is the case in many other emerging markets. The supply of alternative funding sources for firm innovation, such as venture capital and private equity, is very limited. For instance, in 2013 the stock of private equity investments stood at just 0.01 percent of GDP, compared to slightly over 1 percent in the U.S. and 0.45 percent in Western Europe.[7]

4 Data

Our identification strategy—outlined in Section 5—requires a detailed picture of the banking landscape around individual firms, the credit constraints these firms experience, and their innovation activities. To this end we merge two new micro datasets.

4.1 Firm-level data

Our firm-level data come from the 5$^{\text{th}}$ round of the Business Environment and Enterprise Performance Survey (BEEPS V) conducted by the European Bank for Reconstruction and Development (EBRD) and the World Bank between August 2011 and October 2012. Face-to-face interviews were held with the owner or main manager of 4,220 firms across Russia with the objective to understand how particular aspects of the business environment hold back firm performance.[8] An important improvement over earlier

[7] Source: Emerging Markets Private Equity Association.

[8] Our sample size is 3,849 as we exclude 38 firms with unknown loan status, 37 firms with a loan from an unknown source, and 296 firms that had applied for a loan but whose application was yet to be

rounds is the comprehensive coverage of BEEPS V, with at least one region covered in each of Russia's federal districts.[9]

4.1.1 Firm innovation

The BEEPS V survey for the first time included an *Innovation Module* to elicit detailed information about firms' innovation activities. This new module covers both the adoption of existing technologies and in-house R&D. We use these data to construct a number of firm-level innovation measures which are summarized in Online Appendix Table A2 (see Table A1 for definitions). The average Russian firm introduced 0.77 innovations in the last three years (*Aggregate innovation*) with 42 (27) percent of the firms implementing at least one (two) innovation(s). The existing literature has often used a definition of *Technological innovation* that only takes product and process innovations into account. We follow this literature as technological innovation may arguably be most affected by credit constraints. About 13 (14) percent of all firms report a *Product (Process) innovation.*

Organization innovation and *Marketing innovation* were more prevalent, with on average 24 and 27 percent of firms engaged in these forms of innovation, respectively. We aggregate these two innovation types into one *Soft innovation* measure. Just over half of all firms had implemented at least one soft innovation over the past three years. Finally, 11 percent of all sampled Russian firms undertook some form of R&D. Our data show that there is substantial variation across as well as within Russian regions in the incidence of these innovation activities. The Online Appendix contains more details about our innovation data.

4.1.2 Firms' access to credit

To assess the impact of bank credit on firm innovation we need an indicator of whether firms are credit constrained or not. To create this measure, we use the BEEPS V data to first distinguish between firms with and without a demand for credit. We then split the former group into those that applied for a loan and those that did not apply

finalized or had been withdrawn. All our findings are robust to the inclusion of these firms.

[9] Russia can be divided into nine federal districts or alternatively into twelve economic zones. The next level of disaggregation consists of regions (so-called federal subjects). The BEEPS V sample framework encompasses non-agricultural firms with at least five employees (fully state-owned firms are excluded). Random sampling with three levels of stratification ensures representativeness across industry, firm size and region. Stratification allows us to use industry fixed effects in all estimations.

because they thought they would be turned down. Finally, among those that applied, we observe which firms were granted credit and which ones were refused a loan. Using this categorization, we follow Guiso, Sapienza, and Zingales (2004) and define credit-constrained firms as those that were either discouraged from applying or were rejected when they applied. Discouraged firms are an important category to capture as they may differ systematically from non-applying firms that do not need a loan. Table A2 indicates that 55 percent of all sample firms needed a loan. Between 52 percent (narrow definition) and 68 percent (broad definition) of these were credit constrained.[10] Just over a quarter of all firms had a loan at the time of the survey.

The BEEPS V survey asks borrowing firms to disclose the name of their lender as well as other loan terms (less than five percent of the firms did not know the name of their lender or did not want to share this information). For each lender we establish whether it is state owned (at least 30 percent of its shares held by municipalities or the central government), foreign owned (at least 50 percent of share capital held by foreigners) or in private domestic hands. For each foreign bank, we also identify the parent bank and its country and city of incorporation. Finally, we link each bank to Bankscope, Bureau van Dijk's database of banks' financial statements. Table A2 shows that 46 percent of all borrowers had a loan from a state bank, 42 percent from a private domestic bank, and 12 percent from a foreign bank.

We also distinguish private banks according to the main lending technique they apply when dealing with SMEs. This distinction is based on information collected through face-to-face interviews with CEOs of private Russian banks as part of the EBRD Banking Environment and Performance Survey (BEPS). CEOs were asked to rate on a five-point scale the importance (frequency of use) of the following techniques when lending to SMEs: relationship lending; fundamental and cash-flow analysis; business collateral; and personal collateral. Although, as expected, almost all private banks find building a relationship (knowledge of the client) of some importance, 42 percent of the interviewed banks find building a relationship "very important", while the rest considers it only "important" or "neither important nor unimportant." We categorize the former group of banks as relationship banks.[11] For 758 out of 1,010 borrowing firms we know whether their lender is a relationship bank, a transaction bank, or a state bank.

[10]The broad definition also includes firms that were discouraged because of complex application procedures or because informal payments were necessary. Throughout our analysis we use this broad definition of credit constraints but our results are robust to using the narrow one (cf. column 1 of Table 5). The Online Appendix contains more details about our firm-level credit variables.

[11]See Beck, Degryse, De Haas and Van Horen (2014) for details about the BEPS survey.

Table 1 provides a first, univariate look at the link between credit constraints and innovation. We divide firms into three categories: those with a loan (1,010 firms), those without a loan and without a need for one (1,555), and those without a loan but with an unfulfilled demand for credit (1,284). The latter group contains all credit-constrained (rejected or discouraged) firms. Among firms that needed credit, there is a striking difference in the likelihood of innovation activity between those that received credit (54.7 percent implemented at least one innovation) and those that did not (40.7 percent). A formal two-sample t-test confirms that this difference in means is statistically significant at the 1 percent level. The lowest incidence of innovation (35.8 percent) occurs among firms that did not demand a loan.

Credit status also correlates with the extent of innovation. Table 1 shows that 38.3 percent (21.0 percent) of borrowing firms introduce at least two (three) different types of innovations, compared with only 24.8 percent (13.1 percent) of the credit-constrained firms. Similarly, firms that have access to credit carry out more innovation as measured by our technological and aggregate indices. All of these differences are highly significant. A clear picture emerges with regard to access to credit and innovative activity: it is mostly those firms that apply for a loan and get one that innovate.

We next examine whether, conditional on borrowing, bank ownership is linked to firm innovation. This does not appear to be the case: innovation at the extensive margin is very similar among borrowers from private domestic banks (52.9 percent), state banks (55.9 percent), and foreign banks (55.9 percent). There is some indication that foreign bank loans are associated with more innovation at the intensive margin, with 43.2 percent of firms borrowing from a foreign bank carrying out at least two innovations compared to 35.3 (39.8) percent of firms that borrow from a private domestic (state) bank. However, formal comparisons fail to reject the null hypothesis of no difference in means across bank types, at least in this univariate setup.

4.2 Geographical data on bank branches

Small business banking remains a local affair despite rapid technological progress and financial innovation.[12] Banks continue to lend mainly to nearby firms to keep transportation and agency costs within check and local variation in the number and type of

[12] See Petersen and Rajan (2002); Guiso, Sapienza and Zingales (2004); Degryse and Ongena (2005) and Butler and Cornaggia (2011).

bank branches may therefore explain why small firms in certain areas are more credit-constrained than similar firms elsewhere. The local nature of small-business lending plays a central role in our identification.

To assess the impact of local banking markets on firms' credit constraints and innovation behavior, we employ new data from the 2nd Banking Environment and Performance Survey (BEPS), conducted by the EBRD in 2012. As part of this survey a team of Russian-speaking consultants collected the geo-coordinates of 45,728 branches of 853 Russian banks. Figure A1 in the Online Appendix shows the distribution of banking and general economic activity across Russia. Panel (a) indicates that economic production is concentrated in the south-west. Panel (b) depicts the location of the 45,728 bank branches in our dataset. A comparison shows that economic and banking activity are spread similarly over the country.

Using this detailed picture of the local banking landscape we can now link each BEEPS firm to the various bank branches that are located in its city or town (locality). This allows us to construct three locality-level banking variables. First, we calculate a Herfindahl-Hirschman Index (HHI) to measure bank concentration in each locality where at least one BEEPS firm is located. There are 159 such localities in our dataset. Following Degryse and Ongena (2005, 2007) we define a bank's local market share as the percentage of branches that it owns in the locality. Let N_b denote the total number of banks in locality k and b denote a bank. We then construct:

$$Bank\,concentration_k = \sum_{n=1}^{N_b} \left(\#branch_b / \sum_{n=1}^{N_b} \#branch_b \right)^2$$

The average value of the HHI, which ranges between 0.04 and 1, is 0.29 (Table A2 and Figure A2).

Second, we measure the local market share of foreign banks. Let F_b denote the total number of foreign banks in locality k. We construct:

$$Share\,foreign\,banks_k = \sum_{f=1}^{F_b} \#branch_b / \sum_{n=1}^{N_b} \#branch_b$$

The market share of foreign banks ranges between zero and 26 percent and averages 10 percent (Table A2 and Figure A2).

Lastly, we create a third locality-level banking variable. We use regional data from

Berkowitz, Hoekstra and Schoors (2014) to measure historical variation in the number of spetsbanks per million inhabitants in each locality for which we have firm-level data. Since the number of localities is greater than the number of regions, we use an interpolation procedure with weights equal to the inverse of the firm's distance to the capital city in its own region as well as the capital cities of its neighbouring regions. The average locality has 1.89 spetsbanks per million inhabitants and the measure varies between 0.16 and 7.45 (Table A2 and Figure A2).[13]

Similar to the historical branching variation exploited by Guiso, Sapienza and Zingales (2004) for the case of Italy, Berkowitz et al. (2014) provide evidence that the geographical concentration of spetsbanks in 1995 was unrelated to drivers of contemporaneous or future economic growth, but instead reflected historical idiosyncrasies that subsequently persisted. We investigate this claim by systematically correlating the number of spetsbanks per million population with a large number of regional firm characteristics (Appendix Figure A3), political and economic indicators (Figure A4 and A5), and proxies for regional democratization (Figure A6). In all cases, we find no strong correlation between these measures and the presence of spetsbanks in 1995. We provide more statistical evidence on the exogeneity of the variation in spetsbank presence in Section 6.5.

5 Methodology

5.1 Empirical model

Our empirical strategy comprises two main steps. First, we assess how local variation in bank ownership, bank concentration, and the historical presence of spetsbanks affect firm-level credit constraints. Second, we analyze how access to credit, or the lack thereof, impacts the probability that a firm innovates. Consider the empirical model:

$$\begin{aligned} Firm\,Innov_{ijk} &= \alpha_1 Cred\,Constr_{ijk} + \mathbf{z}_{1,ijk}\delta_1 + \eta_j + u_{ijk} && (1) \\ Cred\,Constr_{ijk} &= \beta_1 Local\,Banking_k + \mathbf{z}_{2,ijk}\delta_2 + \eta_j + v_{ijk} && (2) \end{aligned}$$

[13] We also create an alternative spetsbank measure that excludes branches that were originally owned by the bank for housing and social development (Zhilsotsbank). One may worry that these branches lend less to firms and may therefore lead us to underestimate the impact of access to credit on firm innovation. Excluding Zhilsotsbank branches does not materially alter any of our results in terms of economic or statistical significance.

for firm i operating in industry j in locality k. $Firm\,Innov_{ijk}$ is either an innovation index (*Technological*, *Soft* or *Aggregate innovation*), an innovation intensity variable (*At least 2 innovation types* or *At least 3 innovation types*) or one of the underlying, detailed indicators of firm innovation. $Cred\ Constr_{ijk}$ is a firm-specific indicator for access to credit as defined in Section 4.1.2, while $LocalBanking_k$ comprises the three geographical banking variables (these variables are not highly correlated with all absolute pairwise correlation coefficients below 0.40).

In the first equation, $\mathbf{z}_{1,ijk}$ is a vector of observable firm covariates that co-determine the probability that a firm innovates (see Section 5.2), while in the second equation $\mathbf{z}_{2,ijk}$ is a vector of observable firm covariates that influence whether a firm is credit constrained. In both equations, η_j is a vector of industry fixed effects that are defined at the ISIC Rev 3.1 2-digit level. These control for unobserved industry variation and ensure that our estimates are not confounded by attributes common to firms in the same industry. They also control for sector-specific innovation opportunities via intra-industry knowledge and technology spill-overs. We are interested in β_1, which can be interpreted as the impact of local credit market conditions on credit constraints in a locality, and α_1, the effect of not having access to credit on innovation.

The model in (1)-(2) is characterized by two complications. First, $Cred\ Constr_{ijk}$ may correlate with the error term in (1), u_{ijk}, if innovating firms are more likely to run into credit constraints. Even if firms do not rely on bank loans for innovation, they may become credit constrained if innovation reduces the internal funds available for subsequent production. This increases the probability that the firm hits a financial constraint and the incidence of innovation can become positively correlated with the reported severity of such constraints. Second, we only observe whether a firm is credit constrained for the sub-sample of firms that indicate they need a loan. Hence, even in the absence of the first complication, $Cred\ Constr_{ijk}$ is potentially correlated with u_{ijk} if the demand for credit is systematically related to u_{ijk}. Either of these complications is enough to render $Cred\ Constr_{ijk}$ endogenous.

Since we do not always observe whether a firm is credit constrained, we can neither estimate β_1 in (2) with an ordinary least squares (OLS) procedure nor get a reliable estimate of α_1 in (1) with two-stage least-squares (2SLS) estimation. However, we do know the conditions under which the $Cred\ Constr_{ijk}$ variable is missing: when a firm does not demand a bank loan. So we complement our empirical model with the following selection equation (Heckman, 1979):

$$Demand\,Loan_{ijk} = 1(\mathbf{z}_{3,ijk}\delta_3 + \eta_j + w_{ijk} > 0) \quad (3)$$

where $\mathbf{z}_{3,ijk}$ is a vector of covariates that determine the probability that a firm needs bank credit. We observe the loan demand status for all firms in the sample.

This setup allows us to follow the two-step procedure outlined in Wooldridge (2002, p. 568) to derive consistent parameter estimates for both α_1 and β_1. We first obtain the inverse Mills' ratio, λ_{ijk}, from a probit estimation of equation (3) using all observations. Second, we use the sub-sample for which we observe both $Firm\,Innov_{ijk}$ and *Cred* $Constr_{ijk}$ and estimate by 2SLS:

$$\begin{aligned} Firm\,Innov_{ijk} &= \alpha_1 Cred\,Constr_{ijk} + \mathbf{z}_{1,ijk}\delta_1 + \gamma_1\lambda_{ijk} + \eta_j + u_{ijk} && (4) \\ Cred\,Constr_{ijk} &= \beta_1 Local\ Banking_k + \mathbf{z}_{2,ijk}\delta_2 + \gamma_2\lambda_{ijk} + \eta_j + v_{ijk} && (5) \end{aligned}$$

where $LocalBanking_k$ are the instruments in (5) and the second stage is (4). This procedure suits our purposes as it accommodates binary endogenous variables without additional assumptions since equation (5) is a linear projection for $Cred\ Constr_{ijk}$.[14] We test the hypothesis that there is no selection by the t-statistic on $\hat{\gamma}_1$.

5.2 Identification

To identify the selection parameters, we include two variables in (3) to determine whether a firm demands credit or not (both variables are subsequently excluded from (4) and (5)). These indicate whether the firm leases fixed assets and whether it receives any subsidies. A firm that leases typically aims to conserve scarce working capital (the capital-preservation motive). Leasing activity may therefore signal that a firm's capital position is tight and that its demand for bank credit is high. As for subsidy use, Popov and Udell (2012) argue that firms that apply for a subsidy reveal a need for external funding.

[14] All results go through when using a bivariate probit estimator, the alternative for a model with both a binary regressor and a binary outcome variable. This robustness reflects that our treatment probability (being credit constrained) is over 50 percent. Chiburis, Das and Lokshin (2012) show that coefficients estimated with linear IV and binary probit models differ less when treatment probabilities are high. Since the authors also show that below 10,000 observations IV confidence intervals tend to be more conservative, we opt for this approach.

In equation (5) we use our three geographical banking variables—*Bank concentration*, *Share foreign banks*, and *Spetsbanks*—as instruments. There exists an extensive literature on the impact of bank competition on firms' access to credit and this literature has long been characterized by two opposing views. On the one hand, there is theory (Pagano, 1993) and evidence (Jayaratne and Strahan, 1996) to suggest that bank competition alleviates credit constraints as more loans become available at better terms. However, other contributions suggest that *less* bank competition may benefit firms, especially more opaque ones, as market power allows banks to forge long-term lending relationships (Ongena and Smith, 2001; Petersen and Rajan, 1994, 1995). A number of papers attempt to reconcile both views. Bonaccorsi di Patti and Dell'Ariccia (2004) show that while banks' market power boosts firm creation in Italy, in particular in opaque industries, additional market power has a negative effect above a certain level. Likewise, Cetorelli and Gambera (2001) use a cross-country dataset to show that bank concentration promotes the growth of sectors that depend on external finance but lowers overall economic growth.

The sign for *Share foreign banks* is a priori undetermined too. A higher local foreign bank presence may limit access to credit if domestic banks have a comparative advantage in reducing information asymmetries vis-à-vis local firms (Mian, 2006). They may then make better lending decisions based on 'soft' information extracted during lending relationships (Berger and Udell, 2002; Petersen and Rajan, 2002). On the other hand, however, foreign banks may apply transaction technologies, such as credit scoring, that effectively use 'hard' information (Berger and Udell, 2006; Beck, Ioannidou and Schäfer, 2012). Finally, we expect a negative effect of *Spetsbanks* on credit constraints as Berkowitz, Hoekstra and Schoors (2014) document a lasting positive impact of the presence of spetsbanks on regional lending.

For all three instruments, the identifying assumption is that the structure of local and regional banking markets is orthogonal to the error term in (4). That is, the local banking structure only affects firm innovation through its impact on the probability that firms are credit constrained. While plausible, this exclusion restriction could be violated if the location of bank branches is not exogenous but related to local factors that also correlate with firm innovation. While we cannot test the validity of the exclusion restrictions directly, we report tests of overidentifying restrictions under the null that our three instruments are valid. Because our third instrument is constructed on the basis of a different rationale—it exploits persistent historical rather than contemporaneous banking variation—these tests for overidentifying restrictions are quite compelling: if one of the instruments is valid, they serve as a test of the validity of the other ones.

We also note that for the *Spetsbanks* instrument there is strong *prima facie* historical evidence, outlined in Berkowitz, Hoekstra and Schoors (2014), suggesting that the geographical dispersion of spetsbanks was mainly determined by bureaucratic forces. The authors also bring a wealth of statistical evidence to bear to support the claim that local spetsbank presence is unrelated to economic, institutional and demographic indicators. Our own analysis in Section 4.2 confirms this claim. The historical persistence in this exogenous branch dispersion still matters as spetsbanks account for over twenty percent of all present-day Russian loans. Moreover, as discussed in Section 3, the historical spetsbank variation also influenced the subsequent entry and location of new commercial bank branches. We return to our identifying assumption in Section 6.5 where we present further evidence on the exogenous nature of our instruments.

5.3 Control variables

We include a set of controls that may affect credit constraints and firm innovation (summary statistics in Table A2). First, we use *Firm size* as measured by the number of full-time employees. Larger companies may benefit more from innovative activities owing to economies of scale. They also tend to be more transparent as their activities are more easily verifiable to banks (Petersen and Rajan, 1994; Berger and Udell, 1998). To control for informational transparency more directly, we include a dummy for whether the firm has its financial statements certified by an external auditor (*External audit*). We also account for firm *Age*: young firms tend to be less transparent than older ones on account of their limited track record (Herrera and Minetti, 2007).

Second, it is important to consider a firm's intrinsic ability to innovate. We include a dummy for whether the firm has a training program for its permanent employees (*Training*); a dummy for whether the establishment uses technology licensed from a foreign company (*Technology license*, this excludes office software); a dummy for whether the firm has an internationally recognized quality certification such as ISO9000 (*Quality certification*); and the number of years that the main manager has worked in the firm's industry (*Manager's experience*). We also control for *State connection*, which indicates whether the firm was previously state owned, is currently partly state-owned, or is a subsidiary of a previously state-owned enterprise. About 9 percent of all firms in our dataset have some state connection (fully state-owned firms were excluded from the BEEPS V sample framework).

Third, we control for firms' incentives to innovate. We include a dummy variable (*National sales*) for whether the market for the firm's main product is national (sold mostly across Russia) or local. Firms often innovate to expand production or increase efficiency in response to investment opportunities. Although industry fixed effects partly capture this, we also control more directly for such opportunities. First, we use a dummy that is one if the firm expects sales to increase over the next year (*Expect higher sales*). Second, we include a dummy that is one if the firm purchased fixed assets over the past year (*Purchased fixed assets*). Investments in equipment or buildings may reflect growth opportunities that make it more likely that a firm introduces one or more innovations.[15]

6 Results

6.1 Credit demand

We first report the results of our Heckman selection equation in Table 2. The dependent variable is a dummy that is one if the firm has a demand for bank credit and zero otherwise. The probit specification includes the variables *Leasing fixed assets* and *Received subsidies* along our standard set of firm covariates. We also include *Bank concentration, Share foreign banks*, and *Spetsbanks*, the locality-level instruments that we use as credit-supply shifters in the next stage of our analysis. We saturate the model with fixed effects for industries and for Russia's nine federal districts.

As expected, both *Leasing fixed assets* and *Received subsidies* are positively and significantly correlated with a firm's demand for credit. Importantly, we find no strong relationship between our local banking structure variables and the *demand* for credit. This gives us additional confidence that these variables are good candidates to identify shifts in the *supply* of credit in the next stage.

6.2 Local banking markets and firms' credit constraints

In Table 3 we present the first-stage of our 2SLS procedure to estimate the impact of the local banking market on firms' credit constraints. The dependent variable in the

[15] Guadalupe, Kuzmina and Thomas (2012) show how Spanish firms acquired by multinationals tend to simultaneously purchase new machinery *and* adopt new innovative production methods.

first stage is *Credit constrained*, a dummy that is one if the firm needed credit but was either rejected or discouraged from applying for a loan. Our three main independent variables are the credit-supply shifters *Bank concentration, Share foreign banks*, and *Spetsbanks.* We include these alongside our battery of standard covariates as well as district and industry fixed effects.

We note that throughout the table the first stage F-statistic is close to or above ten, indicating that our instruments are sufficiently strong. The soundness of our identification strategy is also grounded in the validity of the instrument set. Hansen over-identification tests show that the null hypothesis that our three instruments are jointly valid cannot be rejected.

Column 1 indicates that a more concentrated local banking market is associated with a lower probability that a firm is credit constrained. A one standard deviation increase in local lender concentration reduces the probability that a firm is constrained by 9.3 percentage points. This suggests that competitive credit markets may prevent banks from establishing long-term lending relationships that benefit small businesses. Indeed, if we would move a firm from a locality characterized by high lender competition—such as central Moscow, where the HHI is 0.04—to a locality with less banking competition—such as Saransk in the Volga region, where the HHI is 0.15—then this firm would have a 3.4 percentage points lower probability of being credit constrained, all else equal.

A higher proportion of foreign-owned bank branches in a locality is also associated with less binding credit constraints. Compared to state banks and private domestic banks, foreign banks appear to be better placed to overcome agency problems in Russia.[16] This effect is quite substantial. The coefficient for *Share foreign banks* implies that a one standard deviation increase in this share reduces the probability of a firm being credit constrained by 10 percentage points. If we would move a firm from Moscow to Rostov, with a share of foreign bank branches of 0.12 and 0.09, respectively, then this would increase the probability of being credit constrained by 4.3 percentage points, all else equal. Lastly, as expected, a higher local presence of spetsbanks is associated with less credit constraints. A one standard deviation increase in the number of spetsbanks per million inhabitants reduces the probability of being credit constrained by 2.7 percentage points.

If we take the results on the positive impact of local bank concentration on credit

[16] Giannetti and Ongena (2009) find for a set of transition countries that foreign bank lending stimulates growth in firm sales and assets although this effect is dampened for small firms.

constraints at face value, then this impact should be stronger for opaque firms, for whom lending relationships are most important. Columns 2-5 in Table 3 provide evidence based on interaction terms between the HHI and a number of firm characteristics that supports this assertion. Local bank concentration reduces credit constraints in particular for smaller firms (column 2), younger firms (column 3), firms without a quality certification (column 4), and unaudited firms (column 5, this coefficient is imprecisely estimated).

We push this idea further in columns 6-8 of Table 3. We now split our firm sample into two industry groups and estimate the impact of bank concentration on credit constraints for each group separately. In column 6 we distinguish between firms in high-tech versus low-tech industries (see Table A1 for the industry classification). In our sample around 20 (80) percent of all firms is part of a high-tech (low-tech) industry. In line with findings by Benfratello et al. (2008) for Italy, who use a similar industry classification, the impact of local lender concentration on credit constraints is almost twice as high in high-tech than in low-tech industries.[17] It is easier for firms in low-tech industries to obtain financing via arm's length lending techniques, and this type of lending tends to perform better in less concentrated lending markets.

In column 7 we distinguish between firms with a high (above median) versus low dependence on external finance. We define external finance dependence by averaging for each industry the proportion of working capital that firms finance through sources other than internal funds or retained earnings (as reported by these firms in the BEEPS V Russia survey). As expected, we find that the impact of lender concentration on credit constraints is more pronounced in industries that rely heavily on external funding. This finding concurs with Nanda and Nicholas (2014) who show that during the Great Depression the negative impact of bank distress on innovation was stronger for U.S. firms that depended heavily on external finance.

Likewise, in column 8 we distinguish between firms in industries characterized by relatively high (above median) levels of tangible assets (properties, plants and equipment) versus firms in industries with below median levels of asset tangibility. This industry classification is only available for manufacturing firms and thus reduces our sample (cf. Aghion and Kharroubi, 2013). The results show that local bank concentration mainly

[17] High-tech industries are characterized by larger information asymmetries and more severe agency problems between borrowers and lenders (Holmstrom, 1989).

alleviates credit constraints among firms without access to easily collateralizable assets. These are exactly the type of firms that one expects to benefit from longer-term lending relationships that tend to flourish in concentrated credit markets. Note that these consistent interaction effects also assuage worries about possible omitted variables bias at the local level (Guiso, Sapienza and Zingales, 2004).

Jointly these findings provide consistent evidence that local credit-market concentration alleviate credit constraints for small and opaque businesses in particular. For instance, column 2 shows that a one standard deviation increase in lender concentration reduces the probability of being credit constrained by 27.6 percentage points for the smallest firms in our sample. This impact gets progressively smaller for larger and older firms. When a firm reaches 232 employees or 22 years of age, lender concentration starts to have a negative impact on access to credit, indicating that larger and older firms benefit from bank competition. A robustness test in Table 5 provides evidence for a more general non-linearity in the impact of banking concentration on access to credit. In the most concentrated credit markets, further concentration hurts access to credit for all types of firms, in line with the results by Bonaccorsi di Patti and Dell'Ariccia (2004) for Italy.[18]

6.3 Credit constraints and firm innovation

Table 4 presents our baseline estimates of the impact of credit constraints on firm innovation as taken from the second stage of our 2SLS approach. *Credit constrained* is the endogenous variable that we instrument as per column 1 of Table 3. We control for various standard innovation determinants as well as industry and district fixed effects.

Column 1 indicates that credit-constrained firms are less likely to innovate at the extensive margin. The impact of credit constraints is large. The estimates in columns 2 and 3 imply that a constrained firm has a 22 (32) percentage points smaller probability of carrying out a product (process) innovation compared with a firm that is not constrained, all else equal. The coefficient is somewhat less precisely estimated for product innovation. Column 4 shows that reduced credit constraints also translate into more organizational and marketing innovation, as aggregated in our *Soft innovation* measure.

[18]We ran similar regressions where we interact *Share foreign banks* with the same set of firm characteristics. These unreported results (available upon request) show that the local presence of foreign banks mainly reduces credit constraints for larger firms and for firms in industries with above median levels of asset tangibility. This indicates that bank concentration and foreign-bank presence tend to benefit different parts of the firm population.

The economically and statistically stronger effect for process innovation is interesting as process innovation may be more difficult to fund with bank loans than product innovation. Firms may worry that banks either disclose proprietary information about new production processes to competitor firms—as in Bhattacharya and Chiesa (1995) and Yosha (1995)—or use such information to hold up the firm (Rajan, 1992). Such issues apply less to product innovation, the results of which are easily observable to buyers and other outsiders. Our findings suggest, however, that access to bank credit facilitates both types of technological innovation. One reason may be that process innovation is often closely linked to investments in new machinery that may be used as collateral (Hall, Lotti and Mairesse, 2009). Yet the positive impact on process (and product) innovation holds even when we control for whether the firm invested in fixed assets over the past three years. It also holds when we exclude firms that both introduced a new process and invested in fixed assets (results available upon request).

The results in the last four columns of Table 4 indicate that less-constrained firms are also more likely to innovate more at the intensive margin. Columns 6 and 7 show that access to credit is associated with a higher likelihood of firms undertaking at least two or three different types of innovative activity (for instance, combining a product with a process innovation). Columns 8 and 9 indicate that there is also a positive effect on the number of new products and processes introduced in each of these innovation categories. The point estimate in column 8 suggests that unconstrained firms introduce on average three new products more than credit-constrained firms do, all else equal.

Improvements in production technologies often depend on concurrent investments in auxiliary systems. Our results suggest that access to bank credit allows firms to invest in such related support systems and hence to exploit the benefits of process innovation more fully. Appendix Table A3 shows that firms that are less credit constrained are not only more likely to improve their core production methods but also to upgrade support services such as purchasing, accounting, and maintenance systems. Moreover, column 4 indicates that access to credit and the resulting changes in production structures mean that firms manage their production more tightly. Firms are less likely to work without any production targets—that is, goals with regard to the quantity, quality, and on-time delivery of output.[19] They also achieve these production targets with less effort (column 6). Taken together, our results suggest that borrowing firms upgrade and better manage their production processes. Such improvements can have significant

[19]These results are based on a smaller sample as the BEEPS V survey only asked manufacturing firms with at least 50 employees about their management practices.

productivity impacts as good management practices—including lean manufacturing processes and performance tracking—are important drivers of firm-level productivity (Bloom and Van Reenen, 2007).

The estimated coefficients for our covariates are in line with the existing literature. The statistically strongest results indicate that innovative activity is higher among dynamic firms that expect higher sales, offer formal labour training, and have recently invested in fixed assets. Large firms—those that operate at the national level—are more likely to innovate too, which is in line with cross-country evidence by Ayyagari et al. (2011). Finally, firms that have a quality certification, license technology from a foreign company, or provide employee training are also more likely to innovate.

6.4 Robustness

In Table 5 we subject our baseline second-stage results to a battery of robustness checks. In each regression the dependent variable is *Technological innovation* as in column 1 of Table 4.[20] First, in column 1 we replace our broad measure of credit constraints with a more narrowly defined variable. This narrow measure does not regard firms that were discouraged from applying for a loan because they thought that banks' procedures were too complex or because they expected to have to pay a bribe as credit constrained. Our results hold and even increase slightly in economic magnitude.

In column 2, we add six firm covariates to further reduce the risk of omitted variables bias. These are dummy variables that indicate whether the establishment is part of a larger firm; is *Foreign-owned*; is an *Exporter*; or is located in the *Main business city* of a region or in another *Large city* (>1 million inhabitants). We also include the *Share of temporary workers*. Only the first of these is precisely estimated, indicating that firms that belong to a larger organization are less likely to innovate, presumably because such larger firms typically innovate at a more centralized level. Importantly, compared to Table 4, we find that the coefficient for *Credit constrained* hardly changes.

Next, in columns 3-7, we use alternative banking indicators instead of the simple HHI index in the first stage of our analysis. In column 3, we use an HHI index where banks' local market share is weighted by the bank's total assets across Russia. In this way we take into account that large banks may have more local market power. In column 4, we use the aggregate market share (in terms of number of branches) of the three largest

[20]We apply all tests to all specifications in Table 4 and find the same level of robustness. For brevity Table 5 only presents the results for *Technological innovation*.

banks in the locality. In column 5, we measure the average profits-to-operating revenue ratio of local banks (weighted by their number of local branches). Higher relative profits, as measured at the national level, may indicate more market power at the local level. Similarly, in column 6 we calculate the branch-weighted average Lerner index for all banks in a locality. In all cases, the negative impact of credit constraints on firm innovation continues to hold. Lastly, in column 7 we add an additional dummy to the first stage to single out localities with an HHI of 0.2 or larger.[21] The first stage, with a higher F-statistic of 12.75, shows that the negative impact of lender concentration on credit constraints turns positive in very concentrated markets.

In columns 8 and 9, we experiment with different fixed effects. Instead of fixed effects at the federal district level, column 8 includes fixed effects for Russia's twelve main economic zones. In column 9, we go a step further and now replace our locality-level instruments in the first stage with locality fixed effects. In both cases, the negative relationship between credit constraints and innovation holds up. The coefficient estimate in column 9 provides a lower bound for the impact of credit constraints on innovation.

In columns 10 to 14, we rerun our baseline regressions on various sub-samples. In column 10, we exclude all firms that are five years or younger. In this way we reduce the probability that recently established firms have sorted endogenously into localities with banking structures that are more conducive to firm innovation. In column 11, we exclude the twenty most innovative localities to make sure that our results are not driven by a few high-innovation clusters. For similar reasons we exclude the three most innovative regions (Samara, Moscow and Voronezh) in column 12. In column 13, we exclude firms in Russia's two main urban agglomerations, Moscow and St. Petersburg, which are also the country's financial centres. Lastly, in column 14, we exclude localities without at least one foreign bank branch. There are only forty of such localities in our dataset (containing 71 surveyed firms), reflecting the extensive branch footprint of foreign banks across Russia. On the basis of all of these alternative sub-samples, our first stage remains strong and we continue to find an economically and statistically significant negative impact of credit constraints on firm innovation.

In columns 15 to 17 we structure our standard errors differently. While in the baseline regressions we present robust standard errors clustered at the industry level, we now cluster at the district level (column 15), regional level (column 16), or—as recommended by Chiburis et al. (2011)—bootstrap the errors (column 17). While this

[21]We choose this cut-off because U.S. anti-trust laws stipulate that a merger can be approved without further investigation if concentration in the post-merger market remains below this level.

somewhat increases the standard errors, in all three cases we continue to find an effect of credit constraints on innovation that is statistically significant at the 5 percent level.

Lastly, in column 18 we re-estimate our baseline model using a limited information maximum likelihood (LIML) estimator, which is less likely to generate bias if the first stage of the IV procedure is relatively weak. Although the F-statistic points to minimal bias from our instruments in the first stage, we want to guard against any possible distortion due to the combination of a relatively small sample size and multiple instruments. Both the LIML estimate and the associated standard errors are only marginally larger than the baseline estimate. Given this similarity, we are comfortable that our first stage does not introduce any distortion to the actual causal effect we aim to identify.

6.5 The exogeneity of local banking markets

An important assumption underlying our analysis is that the structure of local banking markets only affects firm innovation through the probability that firms are credit constrained. While plausible, this restriction may not hold if the location of bank branches is related to unobserved local factors that correlate with firm innovation. While we cannot test the validity of the exclusion restriction directly, our analysis so far has produced some reassuring evidence. Tests of overidentifying restrictions consistently cannot reject the null that our three instruments are valid. These instruments—which we effectively use as local credit supply shifters—also appear to be unrelated to credit demand. For the *Spetsbanks* instrument there is strong historical evidence to suggest that the geographical dispersion of these banks was determined by bureaucratic rather than economic considerations. This section provides four additional pieces of evidence to mitigate endogeneity concerns.

First, one may worry that banks opened (more) branches in regions that at present tend to be more conducive to innovation. We therefore collect time-series data from the Russian central bank on regional banking and correlate the regional change in the number of credit institutions between 2002 and 2011 with innovation activity in 2012. We measure regional innovation as the percentage of firms that were involved in product or process innovation. For both innovation types there is a positive but statistically insignificant correlation with the establishment of new banks in the preceding decade (p-values of 0.24 and 0.60, respectively).

Second, we run locality-level regressions where the dependent variable is either *Bank concentration*, *Share foreign banks*, or *Spetsbanks*. We then assess to what extent a battery of locality-level firm characteristics can explain local banking structures. If the banking structure is driven by the composition of the local business sector, then we should find significant relationships between our firm characteristics, averaged at the locality level, and our banking instruments. However, Appendix Table A4 indicates that there is no significant correlation between, on the one hand, the share of large firms, share of audited firms, average firm age, share of exporters, share of firms with access to high speed internet, share of firms that experienced a power cut during the last year, and the average firm's perception of various aspects of the local business environment (local security, political instability, and skills level of the local workforce) and, on the other hand, banking concentration, the presence of foreign banks, or historical variation in the presence of spetsbanks. When we conduct an F-test for the joint significance of these locality-level firm characteristics, we cannot reject the null of no systematic relationship with the local banking structure. Credit-market characteristics thus appear unrelated to a large set of *observable* characteristics of the local business sector.

In Appendix Table A5 we perform a similar exercise to analyze the correlation between regional spetsbank density and a battery of regional political and economic variables (taken from Bruno, Bytchkova and Estrin, 2013). We do this separately for measurements of these variables over 1996-2000, 2001-2004 and 2005-2008. We do not find any evidence of a systematic relationship between local institutions and the presence of spetsbanks. This supports the assertion by Berkowitz, Hoekstra and Schoors (2014) that the historical variation in spetsbank density is orthogonal to economic fundamentals that could have impacted regional economic growth.

Third, while we control for a large number of firm-level, locality-level, and regional-level observable characteristics throughout our analysis, remaining *unobservables* may linger to generate a direct effect of local banking on firms' propensity to innovate. In Appendix Table A6 we therefore use the methodology developed by Altonji, Elder and Taber (2005) and Bellows and Miguel (2009) to quantify the importance of omitted variable bias. Intuitively, what we do is to analyze how the coefficient for *Credit constrained* changes when we include a rich set of firm-level and locality-level covariates. If this change is substantial then it is more likely that adding more (currently unobservable) covariates would further reduce the estimated impact. In contrast, if the coefficient turns out to be stable when adding controls, then we can be more confident when interpreting our results in a causal sense. We measure coefficient stability as the ratio between the value of the coefficient in the regression including controls (numerator) and the difference between this coefficient and the one derived from a regression without covariates (denominator). This shows how strong the covariance between the unobserved factors explaining firm innovation on the one hand and firms' credit constraints on the other hand needs to be, relative to the covariance between observable factors and firms' credit constraints, to explain away the entire effect we find.

The odd columns in Table A6 replicate our baseline regressions of Table 4 while the even columns also include the following locality-level controls: average distance of bank branches to their national HQs; average equity-to-assets ratio of banks (weighted by the number of branches of each bank); bank branch density; share of firms with high-speed internet; share of firms that experienced a power cut in the past year; and five variables that measure the locality-level average of firms' perceptions of the following business constraints: security, business licensing, political instability, courts and education (Appendix Table A1 contains exact definitions). The ratios in the odd columns then compare our baseline specification (as shown in these columns) to an (unreported) specification without any firm controls. The ratios in the even columns compare a specification with firm *and* localityy-level controls (as shown in the even columns) to an (unreported) specification with neither firm nor locality controls.

The Altonji ratios suggest that to explain away the full impact of credit constraints on firm innovation, the covariance between unobserved factors and firms' access to credit needs to be at least 2.9 times as high as the covariance of the included controls (column 4). For *Technological innovation* the ratio lies even around 15. By way of comparison, Altonji et al. (2005) estimate a ratio of 3.55 which they interpret as evidence that unobservables are unlikely to explain the entire effect they document. The negative ratios in columns 2, 5 and 6 reflect that here the coefficient for *Credit constrained* actually slightly increases when we add firm or locality covariates, suggesting that our estimates somewhat underestimate the true causal effect. We conclude that it is unlikely that unobserved heterogeneity explains away the impacts we document.

Fourth, we analyze the sensitivity of our core results to a gradual relaxation of the strict exogeneity assumption that we imposed so far.[22] In particular, we follow the local-to-zero approximation method of Conley, Hansen and Rossi (2012) and allow for a small positive and direct effect of local banking on firm innovation. We view this direct effect

[22] There are two reasons why this relaxation may have a limited impact. First, the fact that local unobservable variation appears to play a minor role mitigates concerns about our instruments being correlated with such unobservables. Second, first-stage F-statistics point to strong instruments throughout our analysis. With strong instruments some violation of the exclusion restriction has less of an effect on the precision of our estimates. See Bound, Jaeger, and Baker (1995) on the trade off between instrument strength and the degree to which the exclusion restriction is violated.

as a random parameter that can be described by a prior distribution. We then obtain frequentist confidence regions that have the correct ex ante coverage under this assumed distribution. We assume that the direct effect of banking concentration and the share of foreign banks on firm innovation is weakly positive. More specifically, we use a uniform prior distribution of $\gamma \in [0, +\delta]^2$ where γ would be the vector of coefficients on the two banking variables in a regression of innovation on credit constraints, the banking variables, and our usual set of controls.

Figure A7 in the Online Appendix plots the 90 percent confidence interval derived from this local-to-zero approximation method for various values of δ. $\delta = 0$ corresponds to the strict exogeneity case, with our point estimate reflecting the value in column 1 of Table 4. As we relax the exclusion restriction with higher values of δ, our point estimate continues to be statistically significant at the 10 percent level. Only at very high values ($\delta > 0.6$) is the coefficient less precisely estimated. However, the impact of being credit constrained on innovation remains around the 0.50 mark, which points to an economically significant effect even under the least stringent assumptions.

7 Extensions

7.1 Credit constraints and the nature of firm innovation

Table 6 exploits the detailed nature of the BEEPS Innovation Module by analyzing the impact of credit constraints on various other innovation outcomes. Since we consider a large number of outcomes, unadjusted p-values may overstate the confidence we can have in any individual estimate. We therefore correct for multiple-hypothesis testing by applying a Bonferroni correction where we consider the outcomes in each of the three panels of Table 6 as a family of related hypotheses. The family-wise error rate is then the probability of at least one Type I error in the family. We limit this error rate to 0.10 by adjusting the p-values that we use to test each individual null hypothesis. We take into account that the outcomes within a family are correlated (see Aker et al., 2012). The inter-variable correlation ranges between 0.2 and 0.4 across the panels. We separately indicate the estimates that are significant at conventional levels and those that also remain significant based on adjusted p-values.

Panels A and B focus on product and process innovation. Columns 1-2 show that the impact of credit constraints on innovation is *not* driven by the adoption of technologies that are also new to the firm's local or national market. While access to credit allows firms to introduce new products and processes, these were typically already available in the market that the firm operates in. This suggests that access to credit helps technologies to diffuse further within but not so much across regional and national borders. This is in line with an earlier literature documenting how technological diffusion depends on the spread of information (Jaffe et al., 2002), which may decline with distance (Mahajan and Peterson, 1985). Firms therefore learn from (and imitate) spatial neighbors in particular (Mansfield, 1961). Our results show how access to credit can facilitate this process of local technological diffusion.

Columns 3 to 5 provide additional insights into *how* firms innovate when they can access bank credit. We find no impact on the development of new products or processes based on the firm's own ideas. Instead, firms tend to make technological advances by actively co-operating with others (column 4). An important strategy is to make significant improvements in production processes with the help of suppliers (this coefficient remains statistically significant at the 1 percent level even after the Bonferroni correction). This tallies with the idea that imports are an important channel of technology diffusion (Keller, 2004).

Column 1 in Panel C shows that with easier access to credit, firms are also more likely to spend funds on the acquisition of external knowledge. This includes the purchasing or licensing of inventions, patents or know-how to start producing a new product or process. Here too, bank credit facilitates the diffusion of technologies across firms. There is also some evidence that access to credit allows firms to attract consultancy know-how, in particular to improve general business skills. However, this estimate is not robust to the Bonferroni correction (Panel C, columns 4 and 5).

In contrast, there is no evidence that bank credit allows firms to undertake more R&D (column 2) or to apply for a patent or trademark (column 3). The absence of an impact of local credit availability on R&D is in line with evidence from Italy (Herrera and Minetti, 2007) and cross-country data (Hsu, Tian and Xu, 2014) but contrasts with the recent literature that links U.S. bank deregulation to increased patenting activity. Our results suggest that bank credit is not well-suited to finance R&D, at least not in an emerging market context where other constraints to R&D may be prevalent too. Note that the absence of an effect of credit on R&D does not simply reflect that Russian firms do not undertake R&D. Both in terms of patents granted and in terms of R&D expenses Russia lags the developed world but leads many other emerging markets.[23]

[23]In 2012, Russia registered 1.4 patents per 1,000 workers, compared with 2.9 in the USA, 4.6 in Germany, and 1.0 in Brazil, China and India. R&D expenses as a percentage of GDP stood at 3.0%

7.2 Bank type and firm innovation

In Appendix Table A7, we limit our sample to firms with a bank loan and investigate whether the type of lender impacts innovation over and above the liquidity effect of the loan. We distinguish between private and state banks and then split the private banks in either foreign versus domestic banks (*Foreign bank*, Panel A) or relationship versus transaction banks (*Relationship bank*, Panel B). We expect a positive coefficient for the *Foreign bank* dummy if foreign banks help borrowers more to adopt products and processes from elsewhere. They may be particularly well-suited to facilitate innovations that are based on imported technologies or that depend on cooperation with foreign suppliers, strategies that the previous sub-section indicated to be important.

We expect relationship lenders to have a competitive advantage in overcoming the information asymmetries associated with firm innovation. However, to the extent that firms fear that relationship lenders may exploit their inside knowledge of the firm's innovative projects, they may be less willing to invest in such innovation in the first place. Hence we only expect a positive coefficient for *Relationship bank* if the superior ability of these banks to overcome information asymmetries is not fully offset by firms' fear of being held up.

The OLS results in Table A7 provide little evidence to suggest that bank ownership or lending techniques play a major role in stimulating firm innovation and technology adoption (beyond the main effect of access to credit). There is nevertheless some statistically weak evidence that borrowers from foreign banks innovate more at the intensive margin (panel A, columns 5 and 6).

A weakness of the OLS results in Table A7 is that they do not account for the endogenous matching between banks and firms. This may obfuscate any underlying impact of bank type on innovation activity. In Table 7, we therefore follow an IV procedure where in the first stage we instrument the foreign-bank dummy with the variable *Closure of banks with regional HQs*. This region-level instrument captures the number of branches of banks headquartered in a region that were closed between January 2004 and January 2006 (per million population). After the December 2003 introduction of the Russian deposit insurance scheme, a large number of bank licenses were unexpectedly revoked by the Russian financial regulator. There was considerable regional variation in the number of branches that were suddenly closed as a result, in

compared with 14.6% in the US, 12.4% in Germany, 2.8% in Brazil, 3.2% in China, and 2.2% in India (sources: PATSTAT and Unesco).

effect leading to regionally varying negative shocks to lending relationships between firms and domestic banks. We exploit this variation to determine the probability that a firm ended up borrowing from a foreign bank. We expect a positive coefficient in this first stage as more domestic bank closures strengthened the local market position of foreign banks.

Column 1 of Table 7 shows that a one standard deviation increase in sudden branch closures is associated with a 4.1 percent higher probability that a firm borrowed from a foreign bank, all else equal. Columns 2 to 8 show the second-stage results. Borrowing from a foreign bank helps firms to introduce new products as well as new marketing and organizational systems (the former result is only significant at the 10 percent level). Borrowers from foreign banks are also more likely to innovate more on the intensive margin (columns 7 and 8). That is, once we account for the endogenous matching between firms and banks, we find that foreign banks display a superior ability to help firms adopt and implement new products and technologies.[24] They may help borrowers access foreign technologies, already used by their foreign clients, and facilitate the subsequent adaptation by granting a loan. Moreover, firms may trust foreign banks more than domestic banks not to disclose proprietary information about new production processes to local competitor firms.

Finally, in Table 8 we analyze whether lender type determines the interest rates that borrowers pay. The results show clearly that state banks charge significantly lower interest rates across the board. This holds when controlling for firm covariates, loan characteristics (maturity, size, presence of collateral), industry and locality fixed effects, and fixed effects for the year in which the loan was issued. The annual interest rate discount provided by state banks amounts to between 0.6 and 1.2 percentage points. This is fairly limited as the average nominal interest rate charged by banks was 14.5 percentage points.

We find no differences in the rates charged by foreign banks versus the benchmark group of private domestic banks (column 1) or in the rates charged by relationship versus transaction banks (column 2). Columns 3 to 8 also reveal no difference between innovating and non-innovating firms in the rates they pay and this again holds across lender types. Interestingly, columns 4, 6, and 8 indicate that innovating firms do pay a mark-up when borrowing from relationship banks. While we caution against over-

[24] In unreported regressions we also test whether state banks perform differently compared to private domestic banks in facilitating firm innovation (again conditional on a loan being in place). We find no such difference.

interpreting this result, it does suggest that banks that are well-suited to extract soft information from innovating firms may exploit this information by charging higher interest rates, as in Rajan (1992). This effect is also quite substantive in economic terms: innovative firms are typically charged over two percentage points more when borrowing from a relationship instead of a transaction lender.

8 Conclusions

We have exploited historical and contemporaneous variation in local credit markets to identify the impact of credit constraints on firm innovation in a large emerging market. Our motivation is the stylized fact that many emerging markets continue to display low levels of technological adoption and hence fail to realize their "advantage of backwardness" (Gerschenkron, 1952). Aghion, Howitt and Mayer-Foulkes (2005) put forward the idea that credit constraints can prevent these countries from exploiting the global pool of available technologies. We use firm-level data to put this idea to the test. Our results show that where banks ease local credit constraints, firms innovate more at the extensive and intensive margin. This finding turns out to be robust to various tests, appears not to be driven by omitted variables bias, and withstands less stringent exogeneity assumptions in our instrumental variables procedure.

Compared with the existing literature, our data allow us to paint a more comprehensive picture of *how* access to bank credit affects firm innovation. We find no direct impact of bank credit on in-house R&D: the role of banks in pushing the technological frontier appears limited. We do find, however, that banks help firms to adopt products and processes that were new to them but that were already available elsewhere in their local market. Firms introduce these new technologies either with the help of suppliers or by simply acquiring external know-how. Better access to bank loans helps firms to manage their production processes more tightly as well. We also present evidence that foreign-owned banks may be particularly well-suited to facilitate such technology adoption. Taken together, these findings indicate that better access to bank credit can facilitate the diffusion of new products and production methods across emerging markets. Without access to sufficient credit, firms can remain stuck in a pattern of low productivity and weak growth, even after other businesses in their country have managed to upgrade their operations.

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The BEEPS V Innovation Module

All questions on innovation in the BEEPS V Innovation Module comply with the OECD guidelines for collecting technological innovation data as laid down in the 3rd edition of the so-called Oslo Manual. The survey also incorporates suggestions by Mairesse and Mohnen (2010) with regard to best practices in innovation survey design.

Firm managers were asked whether during the past three years they introduced new products or services (product innovation); production methods (process innovation); organizational practices or structures (organization innovation); marketing methods (marketing innovation); or conducted R&D. The Oslo Manual defines these types of innovation, a classification that dates back to Schumpeter (1934), in more detail. A product innovation involves the introduction of a good or service that is new or significantly improved with respect to its characteristics or intended uses. This includes significant improvements in technical specifications, components and materials, incorporated software, or other functional characteristics. A process innovation is the implementation of a new or significantly improved production or delivery method. Here one can think of significant changes in production techniques, equipment, software, or logistical methods. Organizational innovation includes significantly improved or new knowledge management, supply-chain management or quality control systems. Marketing innovation relates to new methods of advertising, product promotion and pricing strategies. Lastly, R&D comprises creative work undertaken on a systematic basis to increase the stock of knowledge and to use this stock to devise new applications.

Interviewees were presented with show cards that contained examples of innovations in each of these categories. It was made clear that "new" meant new to the firm but not necessarily new to the local, national or international market. Firms that had undertaken at least one form of innovation were asked detailed questions on the nature of this innovation. A verbatim description of the main innovative product or process (if any) was noted down by the interviewer. All verbatim innovation descriptions were carefully checked by a team of independent evaluators to ensure that we only consider innovations in line with the OECD guidelines. For instance, product customization is not innovation unless characteristics are introduced that differ significantly from existing products. The reader is referred to Schweiger and Zacchia (2014) for more details on data cleaning.

Constructing firm-level indicators of credit constraints

We follow Popov and Udell (2012) to construct our firm-level credit variables and we consider BEEPS question K16: "*Did the establishment apply for any loans or lines of credit in the last fiscal year?*". For firms that answered "*No*", we go to question K17, which asks: "*What was the main reason the establishment did not apply for any line of credit or loan in the last fiscal year*?" For firms that answered "*Yes*", question K18a subsequently asks: "*In the last fiscal year, did this establishment apply for any new loans or new credit lines that were rejected?*" We classify firms that answered "*No need for a loan*" to K17 as unconstrained, while we classify firms as constrained if they either answered "*Yes*" to K18a or answered "*Interest rates are not favorable*"; "*Collateral requirements are too high*"; "*Size of loan and maturity are insufficient*"; or "*Did not think it would be approved*" to K17.

Table 1

Access to bank credit and firm innovation: Univariate results

This table reports univariate results on the relationship between access to bank credit and firm innovation in Russia. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively, for a two-sample t-test of a difference in means with unequal variances. For the t-tests we compare innovation activity among all firms with a loan (top row) to all credit-constrained firms (penultimate row). Table A1 in the Appendix provides variable definitions.

		Share of firms with:			*Average no. of innovations:*		
		Any innovation	At least 2 innovation types	At least 3 innovation types	Technological innovation	Aggregate innovation	Observations
		(1)	(2)	(3)	(4)	(5)	(6)
Firm has a loan		54.65%***	38.32%***	20.99%***	0.38***	1.09***	1,010
	Private domestic bank	52.94%	35.29%	20.00%	0.38	1.03	425
	State bank	55.89%	39.83%	21.63%	0.37	1.11	467
	Foreign bank	55.92%	43.22%	22.03%	0.39	1.19	118
No loan		37.97%	23.04%	11.38%	0.23	0.66	2,839
	No demand	35.76%	21.61%	9.97%	0.21	0.63	1,555
	Credit constrained	40.65%	24.77%	13.08%	0.25	0.70	1,284
Total		42.35%	27.05%	13.90%	0.27	0.77	3,849

Table 2

Determinants of firms' credit demand

This table reports a first-stage probit Heckman selection regression where *Leasing fixed assets* and *Received subsidies* are demand shifters that are excluded in the subsequent analysis. The dependent variable is a dummy equal to '1' if the firm needed bank credit; '0' otherwise. The regression includes industry and district fixed effects, a constant, and the same firm controls as in Table 4. Robust standard errors are clustered by industry and shown in parentheses. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively. Appendix Table A1 contains all variable definitions.

Dependent variable: Loan demand	(1)
Leasing fixed assets (0/1)	0.3119***
	(0.0444)
Received subsidies (0/1)	0.1767**
	(0.0839)
Bank concentration	0.2373
	(0.2756)
Share foreign banks	0.5901
	(0.8856)
Spetsbanks	-0.0274*
	(0.0153)
Industry fixed effects	Yes
District fixed effects	Yes
Firm controls	Yes
Observations	3,754
Pseudo R-squared	0.038

Table 3

Local credit markets and firms' credit constraints across Russia

This table reports results from regressions to estimate the impact of the composition of local banking markets on firms' credit constraints (the first stage of our IV estimation). The dependent variable is a dummy equal to '1' if the firm is credit constrained (broad definition) and '0' otherwise. The inverse Mills' ratio in column 1 is derived from the probit model in Table 2 and from analogous probit models for the other columns. All regressions include a set of firm-level control variables, industry and district fixed effects, and a constant. Controls include (log) *Firm size* , (log) *Firm age* , *External audit* , *Training* , *Technology license* , *Quality certification* , *National sales* , *Expect higher sales* , *Purchasing fixed assets* , (log) *Manager's experience* and *State connection* . Robust standard errors are clustered at the industry level and shown in parentheses. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively. The F-statistic on IVs is for the F-test that the instruments are jointly insignificant, while the p-value of the Hansen J-statistic is for the overidentification test that the instruments are valid. See Table A1 in the Appendix for all variable definitions.

Dependent variable: Credit constrained	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bank concentration	-0.3137**	-0.9546***	-1.1051***	-0.3682**	-0.3955**			
	(0.1456)	(0.2311)	(0.2893)	(0.1555)	(0.1570)			
Share foreign banks	-1.4237***	-1.4047***	-1.4020***	-1.4042***	-1.4037***	-1.4406***	-1.4287***	-1.2802**
	(0.3166)	(0.3151)	(0.3217)	(0.3246)	(0.3113)	(0.3112)	(0.3149)	(0.5291)
Spetsbanks	-0.0205***	-0.0199***	-0.0205***	-0.0205***	-0.0200***	-0.0206***	-0.0207***	-0.0161
	(0.0066)	(0.0068)	(0.0066)	(0.0066)	(0.0067)	(0.0066)	(0.0065)	(0.0126)
Bank concentration * (log) Firm size		0.1752***						
		(0.0548)						
Bank concentration * (log) Firm age			0.3544***					
			(0.1160)					
Bank concentration * Quality certification (0/1)				0.4136**				
				(0.1804)				
Bank concentration * External audit (0/1)					0.2651			
					(0.1651)			
Bank concentration * Low-tech industry (0/1)						-0.2937*		
						(0.1520)		
Bank concentration * High-tech industry (0/1)						-0.5636*		
						(0.2827)		
Bank concentration * Low external finance dependence (0/1)							-0.2090	
							(0.1834)	
Bank concentration * High external finance dependence (0/1)							-0.4334***	
							(0.1200)	
Bank concentration * Low-tangibility industry (0/1)								-0.7711***
								(0.2621)
Bank concentration * High-tangibility industry (0/1)								-0.1427
								(0.2422)
Inverse Mills' ratio	0.3858***	0.3752***	0.3820***	0.3983***	0.3811***	0.3838***	0.3822***	0.4438**
	(0.1250)	(0.1239)	(0.1236)	(0.1219)	(0.1236)	(0.1253)	(0.1276)	(0.2120)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,089	2,089	2,089	2,089	2,089	2,089	2,089	760
F-statistic on IVs	10.51	14.48	17.80	9.60	8.02	8.20	9.73	3.90
Hansen J-statistic (p-value)	0.63	0.68	0.69	0.68	0.71	0.79	0.73	0.61

Table 4

Credit constraints and firm innovation across Russia

This table reports results of regressions to estimate the impact of credit constraints on firm innovation. This is the second stage of our IV estimation; first stage results are reported in column 1 of Table 3. *Credit constrained* (0/1) is the endogenous variable, instrumented as in column (1) of Table 3. The inverse Mills' ratio is derived from the probit model in column 1 of Table 2 and from analogous probit models for the other columns. All regressions include industry and district fixed effects and a constant. Robust standard errors are clustered at the industry level and given in parentheses; *, **, *** indicate significance at the 10%, 5% and 1% level, respectively. Table A1 in the Appendix contains all variable definitions.

	Extensive margin					*Intensive margin*			
Dependent variable:	Technological innovation	Product innovation	Process innovation	Soft innovation	Aggregate innovation	At least 2 innovation types	At least 3 innovation types	Number of new products	Number of new processes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Credit constrained (0/1)	-0.5470***	-0.2237*	-0.3233**	-0.7569***	-1.2928***	-0.4953***	-0.4017***	-3.1181*	-1.0277***
	(0.1720)	(0.1190)	(0.1400)	(0.2862)	(0.4001)	(0.1902)	(0.1353)	(1.6827)	(0.2914)
(log) Firm size	-0.0509**	-0.0241	-0.0268	-0.0323	-0.0800	-0.0263	-0.0282	-0.2604	-0.0721*
	(0.0244)	(0.0156)	(0.0171)	(0.0417)	(0.0551)	(0.0278)	(0.0176)	(0.3062)	(0.0377)
(log) Firm age	0.0420**	0.0258*	0.0162	0.0119	0.0574	0.0263*	0.0239	0.3001	-0.0138
	(0.0203)	(0.0137)	(0.0105)	(0.0291)	(0.0406)	(0.0142)	(0.0153)	(0.4191)	(0.0228)
External audit (0/1)	0.0339	0.0290	0.0049	0.0425	0.0752	0.0001	0.0162	0.7176*	0.0246
	(0.0432)	(0.0269)	(0.0242)	(0.0544)	(0.0817)	(0.0288)	(0.0276)	(0.4044)	(0.0500)
Training (0/1)	0.0721***	0.0278*	0.0443***	0.1954***	0.2682***	0.1081***	0.0763***	0.0713	0.1730***
	(0.0214)	(0.0166)	(0.0093)	(0.0291)	(0.0425)	(0.0205)	(0.0164)	(0.2411)	(0.0369)
Technology license (0/1)	0.0360	0.0559***	-0.0199	0.2123**	0.2507**	0.0821**	0.0858***	0.9960	0.1622**
	(0.0349)	(0.0181)	(0.0291)	(0.0849)	(0.0999)	(0.0395)	(0.0232)	(0.8658)	(0.0677)
Quality certification (0/1)	0.1008	0.0293	0.0716**	0.1129*	0.2073*	0.0651*	0.0915**	0.4500	0.1790*
	(0.0643)	(0.0372)	(0.0349)	(0.0654)	(0.1136)	(0.0393)	(0.0437)	(0.8834)	(0.0979)
National sales (0/1)	0.1018**	0.0457*	0.0561**	0.0603	0.1613**	0.0733***	0.0595***	1.1582***	0.0942*
	(0.0408)	(0.0272)	(0.0226)	(0.0402)	(0.0646)	(0.0273)	(0.0198)	(0.4427)	(0.0535)
Expect higher sales (0/1)	0.0857**	0.0372*	0.0485**	0.1411***	0.2242***	0.0983***	0.0463***	0.4434	0.1275***
	(0.0362)	(0.0210)	(0.0224)	(0.0367)	(0.0589)	(0.0214)	(0.0169)	(0.2751)	(0.0452)
Purchasing fixed assets (0/1)	0.0875**	0.0268	0.0607***	0.1021*	0.1891**	0.0793***	0.0440***	0.1284	0.1353**
	(0.0348)	(0.0271)	(0.0227)	(0.0618)	(0.0816)	(0.0252)	(0.0157)	(0.2007)	(0.0674)
(log) Manager's experience	0.0401	0.0259*	0.0143	-0.0042	0.0371	0.0005	-0.0020	-0.1337	0.0298
	(0.0252)	(0.0143)	(0.0161)	(0.0229)	(0.0404)	(0.0115)	(0.0130)	(0.3200)	(0.0327)
State connection (0/1)	-0.0768	-0.0464	-0.0304	-0.1172	-0.2098	-0.0747	-0.0493	0.7572	-0.0453
	(0.0500)	(0.0299)	(0.0291)	(0.0891)	(0.1291)	(0.0505)	(0.0390)	(1.1284)	(0.0875)
Inverse Mills' ratio	0.4554***	0.1788	0.2766**	0.3508	0.8269**	0.4121***	0.2990***	2.4508	0.3288
	(0.1679)	(0.1127)	(0.1101)	(0.2912)	(0.3792)	(0.1552)	(0.1128)	(2.7261)	(0.2250)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,089	2,089	2,089	2,070	2,070	2,089	2,089	2,089	2,089

Table 5

Robustness tests

This table reports results from alternative specifications of our baseline model (Table 4, column 1). The dependent variable is *Technological innovation* . The Heckman selection equation and the IV first stage are not reported; key first-stage statistics are presented in the last two rows. The first stage of our IV estimation is analogous to column 1 of Table 3, except for columns 3-7 and 9. In columns 3-7, we use alternative measures for banking competition and in column 9 we use locality dummies as instruments. The *Credit constrained* variable is defined as before, except in column 1 where it is defined according to the narrow definition. All regressions include the following standard firm controls: (log) *Firm size* , (log) *Firm age* , *External audit* , *Training* , *Technology license* , *Quality certification* , *National sales* , *Expect higher sales* , *Purchasing fixed assets* , (log) *Manager's experience* and *State connection* . Column 2 also controls for being *Part of a larger firm* , being a *Foreign-owned firm* , being an *Exporter* , *Share of temporary workers* , and whether firm is in the *Main business city* of the region or in a *Large city,* defined as having >1 million people. All regressions include the inverse Mills' ratio, industry fixed effects, firm controls and a constant. District fixed effects are included in all regressions except columns 8-9. The inverse Mills' ratio is derived from a probit model of credit demand as in Table 2. Robust standard errors are clustered at the industry level and shown in parentheses except in columns 14 and 15 where we cluster at the district and regional level, respectively. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively. The F-statistic on IVs is for the F-test that the instruments are jointly insignificant, while the p-value of the Hansen J-statistic is for the overidentification test that the instruments are valid. Table A1 in the Appendix contains all variable definitions.

Dependent variable:	**Technological innovation**																	
	Alternative variables		*Alternative instruments*					*Fixed effects*		*Sub-sample estimation*					*Standard errors*			*Alternative estimator*
	Narrow credit constrained definition	Additional firm controls	Bank concentration (asset weighted)	Share of top 3 banks	Profits / operating revenue	Lerner index	Nonlinear effect of credit market concentration	Economic zones	Locality fixed effects	Excluding young firms (<6 years)	Excl. 20 most innovative localities	Excl. three most innovative regions	Excl. Moscow & St. Petersburg	Excl. localities w/o foreign banks	Clustering at district level	Clustering at regional level	Boot-strapped standard errors	LIML
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Credit constrained (0/1)	-0.6787**	-0.5537***	-0.5610***	-0.3883**	-0.6538***	-0.5436***	-0.4020**	-1.0723***	-0.3009***	-0.6172***	-0.5608***	-0.3772**	-0.6183***	-0.6109***	-0.5470**	-0.5470***	-0.5470**	-0.5600***
	(0.2735)	(0.1895)	(0.1847)	(0.1646)	(0.2029)	(0.1692)	(0.1795)	(0.3424)	(0.0672)	(0.1881)	(0.1819)	(0.1515)	(0.2162)	(0.2099)	(0.2513)	(0.2047)	(0.2279)	(0.1778)
Part of large firm (0/1)		-0.0733*																
		(0.0414)																
Foreign-owned firm (0/1)		0.0809																
		(0.0939)																
Exporter (0/1)		0.0875																
		(0.0590)																
Share of temporary workers		0.0131																
		(0.0239)																
Main business city (0/1)		0.0506																
		(0.0612)																
Large city (0/1)		0.0477																
		(0.0381)																
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inverse Mills' ratio	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,089	2,054	2,089	2,089	2,089	2,089	2,089	2,089	2,011	1,604	2,067	1,867	1,934	2,046	2,089	2,089	2,089	2,089
First-stage statistics:																		
F-statistic on IVs	9.54	9.01	9.04	15.01	8.74	8.75	12.75	4.84	473.46	9.64	12.93	16.82	9.07	8.17	13.37	7.73	12.00	10.51
Hansen J-statistic (p-value)	0.72	0.51	0.56	0.46	0.35	0.54	0.11	0.96	0.005	0.79	0.54	0.21	0.65	0.67	0.63	0.63	-	0.66

Table 6

Credit constraints and the nature of firm innovation

This table reports results of regressions to estimate the impact of credit constraints on firm innovation. This is the second stage of our IV estimation. *Credit constrained* (0/1) is the endogenous variable, instrumented as in column 1 of Table 3. The inverse Mills' ratio is derived from the probit model in Table 2, column 1 and from analogous probit models for the other columns. All regressions include industry and district fixed effects and a constant. Robust standard errors are clustered at the industry level and given in parentheses; *, **, *** indicate significance at the 10%, 5% and 1% level, respectively. †, ††, and ††† indicate significance at the 10%, 5% and 1% level, respectively, when adjusting for multiple-hypothesis testing via a Bonferroni correction where the outcomes in each panel are part of one family. Table A1 in the Appendix contains all variable definitions.

Panel A: Product innovation					
Dependent variable:	New to local market	New to national market	Developed with firm's own ideas	Developed with others	Developed with suppliers
	(1)	(2)	(3)	(4)	(5)
Credit constrained (0/1)	-0.1287	-0.0260	0.0055	-0.2292**	-0.0736
	(0.1013)	(0.0806)	(0.0977)	(0.0937)††	(0.0511)
Panel B: Process innovation					
Dependent variable:	New to local market	New to national market	Developed with firm's own ideas	Developed with others	Developed with suppliers
	(1)	(2)	(3)	(4)	(5)
Credit constrained (0/1)	-0.1972*	-0.0509	0.0270	-0.3503***	-0.1723***
	(0.1011)	(0.0563)	(0.0896)	(0.1163)††	(0.0554)†††
Panel C: R&D and acquisition of external knowledge					
Dependent variable:	Spent on external knowledge	R&D	Applied for a patent or trademark	Hired local consultant	Consulting: business skills improvements
	(1)	(2)	(3)	(4)	(5)
Credit constrained (0/1)	-0.1797***	0.0017	0.0033	-0.2703**	-0.2723*
	(0.0672)††	(0.0726)	(0.0753)	(0.1274)	(0.1508)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes
Inverse Mills' ratio	Yes	Yes	Yes	Yes	Yes
Observations	2,089	2,089	2,089	2,082	2,089

Table 7

Borrowing from a foreign bank and firm innovation

This table reports IV regression results on the relationship between foreign bank ownership and firm innovation. *Closure of banks with regional HQs* measures the number of branches of banks headquartered in a region that were closed between January 2004 and January 2006, per million population. All regressions include industry and district fixed effects, firm controls and a constant. Firm controls include a dummy for borrowing from a state bank. The F-statistic on IVs is for the F-test that the instrument is insignificant. Robust standard errors are clustered at the industry level and shown in parentheses. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively. Table A1 in the Appendix contains all variable definitions.

	First stage	*Second stage*						
Dependent variable:	Loan from foreign bank (0/1)	Technological innovation	Product innovation	Process innovation	Soft innovation	Aggregate innovation	At least 2 innovation types	At least 3 innovation types
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Loan from foreign bank (0/1)		1.2674*	0.9837*	0.2837	4.2838**	5.5521**	1.8400**	0.7970*
		(0.7572)	(0.5801)	(0.4488)	(1.9712)	(2.3366)	(0.7808)	(0.4096)
Closure of banks with regional HQs	0.0160***							
	(0.0055)							
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,026	1,026	1,026	1,026	1,017	1,017	1,026	1,026
F-statistic on IVs	8.48							

Table 8

Lender type, innovation and the cost of borrowing

This table reports regression results on the relationship between lender type, innovation activity and borrowing cost. *Innovation* stands for *Technological innovation* in columns (1)-(4), for *Product innovation* in columns (5) and (6), and for *Process innovation* in columns (7) and (8). Interaction terms with *Innovation* are similarly defined. All regressions include industry, locality and year fixed effects, firm controls and a constant. Robust standard errors are clustered at the industry level and shown in parentheses. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively. Table A1 in the Appendix contains all variable definitions.

Dependent variable:	**Annual interest rate (%)**							
	Technological innovation				*Product innovation*		*Process innovation*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
State bank	-0.6623**	-1.0238**	-0.6746**	-1.0924*	-0.5296*	-0.9116*	-0.8003**	-1.1902**
	(0.3115)	(0.4995)	(0.2775)	(0.5533)	(0.2856)	(0.5357)	(0.3301)	(0.5317)
Foreign bank	0.6873		0.4486		0.5830		0.4728	
	(0.6278)		(0.6140)		(0.5745)		(0.6397)	
Relationship bank		-0.1926		-0.7238		-0.5679		-0.5967
		(0.7843)		(0.6818)		(0.6802)		(0.7186)
Innovation			0.0964	-0.1311	0.3028	-0.0405	-0.0773	-0.4305
			(0.3815)	(0.3987)	(0.8088)	(0.7162)	(0.6006)	(0.6301)
Innovation * State bank			0.0351	0.2798	-0.7950	-0.4063	0.6957	0.9850
			(0.4358)	(0.4697)	(0.8565)	(1.0812)	(0.7891)	(0.8026)
Innovation * Foreign bank			0.6556		0.7780		0.9734	
			(0.8485)		(1.0590)		(1.4503)	
Innovation * Relationship bank				1.7580**		2.7577***		2.4734*
				(0.7619)		(0.9515)		(1.2808)
Loan maturity (log)	0.5330**	0.5647*	0.5451**	0.5508*	0.5276**	0.5461*	0.5464**	0.5649*
	(0.2505)	(0.3244)	(0.2416)	(0.3199)	(0.2453)	(0.3209)	(0.2460)	(0.3256)
Collateral required (0/1)	0.9237	0.7889*	0.9574	0.8512*	0.9556	0.8008	0.9696	0.8829*
	(0.6659)	(0.4524)	(0.6571)	(0.4477)	(0.6747)	(0.4862)	(0.6579)	(0.4349)
Loan size (log)	-0.3994***	-0.3492**	-0.3938***	-0.3543***	-0.3973***	-0.3558***	-0.3907***	-0.3470**
	(0.1286)	(0.1380)	(0.1227)	(0.1240)	(0.1252)	(0.1274)	(0.1285)	(0.1333)
Locality fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan issue year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	589	436	589	436	589	436	589	436
R-squared	0.4705	0.5281	0.4721	0.5376	0.4726	0.5368	0.4728	0.5355

Table A1
Variable definitions and data sources

Variable	Definition	Data source
Innovation activity		
Product innovation (0/1)	Dummy=1 if the firm introduced a new or significantly improved product or service in the last three years; 0 otherwise.	BEEPS V
Process innovation (0/1)	Dummy=1 if the firm introduced a new or significantly improved method for the production or supply of products or services in the last three years; 0 otherwise.	BEEPS V
Organization innovation (0/1)	Dummy=1 if the firm introduced a new or significantly improved organizational or management practice or structure in the last three years; 0 otherwise.	BEEPS V
Marketing innovation (0/1)	Dummy=1 if the firm introduced a new or significantly improved marketing method in the last three years; 0 otherwise.	BEEPS V
R&D (0/1)	Dummy=1 if the firm invested in R&D in the last three years; 0 otherwise.	BEEPS V
At least 2 (3) innovation types (0/1)	Dummy=1 if the firm introduced two (three) or more of the following innovation types: product, process, organization or marketing innovation; 0 otherwise.	BEEPS V
Technological innovation	Sum of the *Product innovation* and *Process innovation* dummy variables.	BEEPS V
Aggregate innovation	Sum of the dummy variables *Product innovation* , *Process innovation* , *Organization innovation* and *Marketing innovation* .	BEEPS V
Soft innovation	Sum of the dummy variables *Organization innovation* and *Marketing innovation* .	BEEPS V
New to local market (0/1)	Dummy=1 if the firm introduced a product (process) innovation that is both new to the firm and its local market in the last 3 years; 0 otherwise.	BEEPS V
New to national market (0/1)	Dummy=1 if firm introduced a product (process) innovation that is both new to the firm and the national (Russian) market in the last 3 years; 0 otherwise.	BEEPS V
Number of products introduced	Number of new or significantly improved products introduced in the last three years.	BEEPS V
Number of processes introduced	Number of new or significantly improved processes introduced in the last three years out of the following categories: production methods, logistics, ancillary support services. This variable thus ranges between 0 and 3.	BEEPS V
Developed with firm's own ideas (0/1)	Dummy=1 if firm introduced a product (process) innovation that it developed or adapted using its own ideas in the last 3 years; 0 otherwise.	BEEPS V
Developed with others (0/1)	Dummy=1 if firm introduced a product (process) innovation that it developed in cooperation with suppliers, clients or external academic or research institutions in the last 3 years; 0 otherwise.	BEEPS V
Developed with suppliers (0/1)	Dummy=1 if firm introduced a product (process) innovation that it developed in cooperation with suppliers in the last three years; 0 otherwise; 0 otherwise.	BEEPS V
Production methods (0/1)	Dummy=1 if the firm over the last three years introduced or significantly improved production methods; 0 otherwise.	BEEPS V
Logistics and delivery (0/1)	Dummy=1 if the firm over the last three years introduced or significantly improved logistics, delivery or distribution methods for it's inputs and products; 0 otherwise.	BEEPS V
Support services (0/1)	Dummy=1 if the firm over the last three years introduced or significantly improved ancillary support services, such as purchasing, accounting, computing and maintenance; 0 otherwise.	BEEPS V
Spent on external knowledge (0/1)	Dummy=1 if firm spent on the acquisition of external knowledge in the last 3 years by purchasing or licensing an invention, patent or know-how in order to start producing a new product (apply a new production method); 0 otherwise	BEEPS V
Applied for a patent or trademark (0/1)	Dummy=1 if firm applied for a patent or trademark in the last three years; 0 otherwise.	BEEPS V
No production target (0/1)	Dummy=1 if firm does not use explicit production targets; 0 otherwise.	BEEPS V
Short-term targets only (0/1)	Dummy=1 if firm only uses short-term production targets (< 1year); 0 otherwise.	BEEPS V
High effort needed (0/1)	Dummy=1 if firm was only able to achieve production targets with more than normal or extraordinary effort; 0 otherwise.	BEEPS V
Hired local consultant (0/1)	Dummy=1 if over the last three years the firm hired at least once a local consultant (such as a management consultant, engineer, architect, accountant); 0 otherwise.	BEEPS V
Consulting: business skills improvements (0/1)	Dummy=1 if over the last three years the firm hired at least once a local consultant to improve business skills (finance, marketing, communication, basic HR, business plans); 0 otherwise.	BEEPS V
Credit access and loan characteristics		
Loan demand (0/1)	Dummy=1 if the firm either applied for a loan or did not apply for a loan for reasons other than it did not need one; 0 otherwise.	BEEPS V
Credit constrained (broad) (0/1)	Dummy=1 if the firm either got a loan application rejected or was discouraged from applying; 0 otherwise. Discouragement reasons: complex application procedures, unfavourable interest rates, too high collateral requirements, insufficient size of loan or maturity, informal payments necessary, belief that application would be rejected.	BEEPS V
Credit constrained (narrow) (0/1)	Dummy=1 if the firm either got a loan application rejected or was discouraged from applying due to the abovementioned reasons except for complex application procedures and informal payments necessary; 0 otherwise.	BEEPS V
Firm has a loan (0/1)	Dummy=1 if the firm has a line of credit or loan from a financial institution at the time of the survey; 0 otherwise.	BEEPS V
Loan from a state bank (0/1)	Dummy=1 if the firm has a loan from a state bank; 0 otherwise.	BEEPS V; BEPS II
Loan from a private domestic bank (0/1)	Dummy=1 if the firm has a loan from a private domestic bank; 0 otherwise.	BEEPS V; BEPS II
Loan from a foreign bank (0/1)	Dummy=1 if the firm has a loan from a foreign bank; 0 otherwise.	BEEPS V; BEPS II

Locality characteristics		
Bank concentration	Locality-level Herfindahl-Hirschmann Index. Market shares measured by branches.	BEPS II
Bank concentration (asset weighted)	Locality-level Herfindahl-Hirschmann Index. Market shares measured by branches and weighted by total assets of each bank.	BEPS II; Bankscope
Share foreign banks	Ratio of foreign-bank branches to the total number of branches in a locality.	BEPS II
Share of top 3 banks	Ratio of branches owned by the largest three banks in the locality (measured by number of branches) to the total number of branches in the locality.	BEPS II
Bank branch density	Number of bank branches per 1,000 inhabitants in the locality.	BEPS II; Rosstat
Spetsbanks	Number of Spetsbanks per million inhabitants in the locality.	Schoors et al. (2014)
Profits/operating revenue (branch weighted)	Branch-weighted profit-to-operating revenue ratio of the banks in the locality.	BEPS II; Bankscope
Lerner index (branch weighted)	Locality-level Lerner index. Branch-weighted average of Lerner index as estimated for each bank at the country level.	BEPS II; Bankscope
Domestic intrabank distance	Average distance of the branches in a locality to their national HQs.	BEPS II
Bank solvency	Average equity-to-assets ratio of banks in a locality (branch weighted).	BEPS II
Closure of banks with regional HQs	Net number of branches of banks headquartered in a region that were closed between January 2004 and January 2006, per million population.	Russian central bank
Security	Average rating by firms in the locality (on a 5-point scale) of the extent to which crime, theft, and disorder are an obstacle to the current operations of the firm.	BEEPS V
Business licensing	Average rating by firms in the locality (on a 5-point scale) of the extent to which acquiring business licensing and permits are an obstacle to the current operations of the firm.	BEEPS V
Political instability	Average rating by firms in the locality (on a 5-point scale) of the extent to which political instability is an obstacle to the current operations of the firm.	BEEPS V
Courts	Average rating by firms in the locality (on a 5-point scale) of the extent to which courts are an obstacle to the current operations of the firm.	BEEPS V
Education	Average rating by firms in the locality (on a 5-point scale) of the extent to which an inadequately educated workforce is an obstacle to the current operations of the firm.	BEEPS V
Power cuts	Share of firms in a locality that experienced a power cut in the past year.	BEEPS V
High-speed internet	Share of firms with a high-speed internet connection on its premises.	BEEPS V
Firm characteristics		
Firm size	Log of number of permanent, full-time workers.	BEEPS V
Firm age	Log of number of years since the firm started operations.	BEEPS V
Leasing fixed assets (0/1)	Dummy=1 if the firm leased any fixed assets, such as machinery, vehicles, equipment, land or buildings in the past fiscal year; 0 otherwise.	BEEPS V
Received subsidies (0/1)	Dummy= 1 if the firm received any subsidies from the national, regional or local governments or European Union sources over the past three years; 0 otherwise.	BEEPS V
External audit (0/1)	Dummy=1 if the firm had its annual financial statements checked and certified by an external auditor in the past fiscal year; 0 otherwise.	BEEPS V
Training (0/1)	Dummy=1 if the firm provided formal training programmes to its permanent, full-time employees in the past fiscal year; 0 otherwise.	BEEPS V
Technology license (0/1)	Dummy=1 if the firm uses at present technology licensed from a foreign-owned company, excluding software; 0 otherwise.	BEEPS V
Quality certification (0/1)	Dummy=1 if the firm has an internationally recognised quality certification (e.g. ISO 9000 or HACP); 0 otherwise.	BEEPS V
National sales (0/1)	Dummy=1 if the firm's main product or service is sold mostly across Russia as opposed to locally or internationally; 0 otherwise.	BEEPS V
Expect higher sales (0/1)	Dummy=1 if the firm expected its annual sales to increase in the next fiscal year; 0 otherwise.	BEEPS V
Purchasing fixed assets (0/1)	Dummy=1 if the firm purchased any fixed assets - such as machinery, vehicles, equipment, land or buildings - in the past fiscal year; 0 otherwise.	BEEPS V
Manager's experience	Log of number of years that the top manager has spent in the industry.	BEEPS V
State connection (0/1)	Dummy=1 if the firm was previously state owned, is currently partly state-owned or a subsidiary of a previously state-owned enterprise.	BEEPS V
Part of large firm (0/1)	Dummy=1 if the firm is owned by a larger enterprise; 0 otherwise.	BEEPS V
Foreign-owned firm (0/1)	Dummy=1 if the firm's equity is partially or fully foreign owned; 0 otherwise.	BEEPS V
Exporter (0/1)	Dummy is1 if the firm exports at least part of its production; 0 otherwise.	
Share of temporary workers	Share of temporary workers in total firm employment in the past fiscal year	BEEPS V
High-tech industry (0/1)	Dummy=1 if the firm belongs to any of the following industries (classification follows ISIC Rev 3.1): 24-chemicals; 29-non-electric machinery; 30-office equipment and computers; 31-electric machinery; 32-electronic material; measuring and communication tools, TV and radio; 33-medical apparels and instruments; 34-vehicles; 35-other transportation; 50-services of motor vehicles; 64-post and telecommunication; and 72-IT; 0 otherwise.	Benfratello et al. (2008)
Low-tech industry (0/1)	Dummy=1 if the firm belongs to an industry not classified as high-tech; 0 otherwise.	
High (low) external-finance dependence (0/1)	Dummy=1 if the firm belongs to an industry with an above (below) median value for external-finance dependence; 0 otherwise. We define external-finance dependence at the 2-digit ISIC Rev 3.1 level by averaging firms' reported proportion of working capital that was financed by sources other than internal funds or retained earnings; 0 otherwise.	BEEPS V
High (low) tangibility industry (0/1)	Dummy= 1 if the firm is in an industry with an above (below) median fraction of assets represented by net property, plant and equipment for US firms in the same industry during 1980–89; 0 otherwise.	Aghion and Kharrubi (2013)

Table A2

Summary statistics

This table presents summary statistics for all variables used in the empirical analysis. Table A1 in the Appendix provides variable definitions and data sources.

	Obs.	Mean	Std. dev.	Min.	Max.
Panel A: Innovation activity					
Product innovation (0/1)	3,887	0.13	0.33	0	1
Process innovation (0/1)	3,887	0.14	0.34	0	1
R&D (0/1)	3,887	0.11	0.31	0	1
Any innovation (0/1)	3,887	0.42	0.49	0	1
At least 2 innovation types (0/1)	3,887	0.27	0.44	0	1
At least 3 innovation types (0/1)	3,887	0.14	0.35	0	1
Technological innovation	3,887	0.27	0.55	0	2
Soft innovation	3,850	0.51	0.77	0	2
Aggregate innovation	3,850	0.77	1.10	0	4
Panel B: Product innovation					
New to local market (0/1)	3,887	0.08	0.28	0	1
New to national market (0/1)	3,887	0.04	0.21	0	1
Number of products introduced	3,887	0.79	5.74	0	10
Developed with firm's own ideas (0/1)	3,887	0.07	0.26	0	1
Developed with others (0/1)	3,887	0.06	0.23	0	1
Developed with suppliers (0/1)	3,887	0.01	0.12	0	1
Panel C: Process innovation					
New to local market (0/1)	3,887	0.08	0.26	0	1
New to national market (0/1)	3,887	0.03	0.17	0	1
Number of processes introduced	3,887	0.37	0.81	0	3
Developed with firm's own ideas (0/1)	3,887	0.06	0.25	0	1
Developed with others (0/1)	3,887	0.07	0.26	0	1
Developed with suppliers (0/1)	3,887	0.02	0.15	0	1
Production methods (0/1)	3,887	0.10	0.30	0	1
Logistics and delivery (0/1)	3,887	0.05	0.23	0	1
Support services (0/1)	3,887	0.07	0.26	0	1
Panel D: Acquiring external knowledge					
Spent on external knowledge (0/1)	3,887	0.06	0.24	0	1
Applied for a patent or trademark (0/1)	3,887	0.06	0.24	0	1
Hired local consultant (0/1)	3,871	0.13	0.34	0	1
Consulting: business skills improvements (0/1)	3,887	0.11	0.31	0	1
Panel E: Access to credit					
Loan demand (0/1)	3,887	0.55	0.50	0	1
Credit constrained (broad) (0/1)	2,138	0.68	0.47	0	1
Credit constrained (narrow) (0/1)	2,138	0.52	0.50	0	1
Firm has a loan (0/1)	3,849	0.26	0.44	0	1
from a state bank	1,010	0.46	0.50	0	1
from a private domestic bank	1,010	0.42	0.49	0	1
from a foreign bank	1,010	0.12	0.32	0	1
from a relationship bank	758	0.16	0.37	0	1
from a transaction bank	758	0.23	0.32	0	1

Panel F: Local banking market characteristics					
Bank concentration	3,887	0.29	0.29	0.04	1
Bank concentration (asset weighted)	3,887	0.19	0.32	0.00	1
Share foreign banks	3,887	0.10	0.07	0.00	0.26
Bank branch density	3,887	0.32	0.14	0.00	1.11
Share of top 3 banks	3,887	0.61	0.24	0.23	1
Spetsbanks	3,887	1.89	1.34	0.16	7.45
Closures of banks with regional HQs	3,887	0.64	1.92	-1.17	10.43
Profits/Operating revenue (branch weighted)	3,887	0.32	0.14	0.00	1.11
Lerner index (branch weighted)	3,887	0.61	0.24	0.23	1.00
Panel G: Firm characteristics					
(log) Firm size	3,881	3.05	1.22	1.39	9.31
(log) Firm age	3,856	2.21	0.69	0	5.16
Leasing fixed assets (0/1)	3,887	0.17	0.38	0	1
Received subsidies (0/1)	3,887	0.04	0.20	0	1
External audit (0/1)	3,887	0.21	0.40	0	1
Training (0/1)	3,887	0.43	0.49	0	1
Technology license (0/1)	3,887	0.07	0.26	0	1
Quality certification (0/1)	3,887	0.11	0.32	0	1
National sales (0/1)	3,887	0.29	0.45	0	1
Expect higher sales (0/1)	3,887	0.50	0.50	0	1
Purchasing fixed assets (0/1)	3,887	0.36	0.48	0	1
(log) Manager's experience	3,777	2.43	0.72	0	4.09
State connection (0/1)	3,887	0.09	0.28	0	1
Part of large firm (0/1)	3,887	0.07	0.26	0	1
Foreign-owned firm (0/1)	3,887	0.03	0.17	0	1
Exporter (0/1)	3,887	0.09	0.29	0	1
Share of temporary workers	3,811	0.14	0.57	0	11.67
High-tech industry (0/1)	3,887	0.19	0.40	0	1
High external finance dependence (0/1)	3,887	0.48	0.50	0	1
High-tangibiliy industry (0/1)	1,265	0.34	0.47	0	1

Table A3

Credit constraints, types of process innovation, and production targets

This table shows regressions to estimate the impact of credit constraints on various types of process innovation and production targets. This is the second stage of our IV estimation where *Credit constrained* (0/1) is instrumented as in column 1 of Table 3. *Production methods* is an indicator variable for firms that introduced new or significantly improved production methods. *Support services* is an indicator variable for firms that introduced new or significantly improved ancillary support services, such as purchasing, accounting, computing and maintenance. *Logistics and delivery* is an indicator variable for firms that introduced new or significantly improved logistics, delivery or distribution methods for the firm's inputs or products. *No production target* is a dummy variable that is "1" if the firm does not use explicit production targets. *Short-term targets only* is a dummy variable that is "1" if the firm only uses short-term production targets (<1 year). *High effort needed* is a dummy variable that is "1" if the firm was only able to achieve its production targets with more than normal or extraordinary effort. An inverse Mills' ratio, derived from the probit model in Table 2, is included. All regressions also include industry and district fixed effects, firm covariates, and a constant. Robust standard errors are clustered at the industry level are shown in parentheses; *, **, *** indicate significance at the 10%, 5% and 1% level, respectively. Table A1 contains all variable definitions.

Dependent variable:	Production methods	Support services	Logistics and delivery	No production target	Short-term targets only	High effort needed
	(1)	(2)	(3)	(4)	(5)	(6)
Credit constrained (0/1)	-0.3368**	-0.2751***	-0.1147	0.4554***	0.3435	-0.5830***
	(0.1535)	(0.0890)	(0.1095)	(0.1196)	(0.2981)	(0.2145)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,089	2,089	2,089	260	260	260

Table A4

Locality characteristics and bank presence

This table shows regressions to estimate the correlation between locality-level characteristics and local banking presence. Locality characteristics: share of large (100+ employees) firms; share of firms that are externally audited; average firm age; share of exporting firms; share of firms with a high-speed internet connection; share of firms that experienced a power cut in the past year; and three variables that measure the locality-level average of firms' perceptions of the following business constraints: security, political instability and education. All regressions include a constant. Robust standard errors are shown in parentheses; *, **, *** indicate significance at the 10%, 5% and 1% level, respectively. Table A1 contains all variable definitions.

Dependent variable:	Bank concentration	Share foreign banks	Spetsbanks
	(1)	(2)	(3)
Large firms	-0.0900	-0.0223	-0.0738
	(0.0963)	(0.0224)	(0.2921)
Audited firms	0.0909	-0.0156	0.0647
	(0.1050)	(0.0223)	(0.4573)
Average firm age	-0.0023	0.0011**	-0.0003
	(0.0015)	(0.0005)	(0.0049)
Exporting firms	0.1316	0.0112	-0.1478
	(0.1719)	(0.0304)	(0.4213)
Share firms with high-speed internet	-0.0212	0.0355	-0.0124
	(0.1105)	(0.0282)	(0.2282)
Share firms with power outages	-0.0543	0.0206	0.3602
	(0.0922)	(0.0200)	(0.2503)
Perceived security	-0.0841	0.0023	0.1427
	(0.0978)	(0.0207)	(0.3901)
Perceived political instability	-0.0400	0.0068	0.1052
	(0.0448)	(0.0085)	(0.1361)
Perceived education workforce	-0.0480	0.0018	0.0005
	(0.0417)	(0.0085)	(0.1098)
Constant	0.6361***	0.0027	1.0444
	(0.2300)	(0.0554)	(0.7966)
F-test for joint significance (p-value)	0.2407	0.2156	0.9354
R-squared	0.0710	0.0790	0.0176
Observations	158	158	158

Table A5

Regional institutional characteristics and spetsbank presence

This table shows regressions to estimate the correlation between regional-level institutional characteristics and the presence of spetsbanks. Each column regresses the number of Spetsbanks per million population in a region on a set of political and economic indicators in that region, measured for three different time periods. Regional political and economic characteristics are taken from Bruno et al. (2013) who source them from Nikolay Petrov and Aleksei Titkov at the Carnegie Moscow Center (http://atlas.socpol.ru/indexes/index_democr.shtml). See Bruno et al. (2013) for a detailed description. All regressions include a constant. Robust standard errors are shown in parentheses; *, **, *** indicate significance at the 10%, 5% and 1% level, respectively.

Dependent variable:	Spetsbanks per region		
Time frame for independent variables:	1996-2000	2001-2004	2005-2008
	(1)	(2)	(3)
Political openness	-0.6497	0.2657	0.7085
	(0.5088)	(0.5345)	(0.4792)
Elections	0.3778	0.0938	-0.3001
	(0.4354)	(0.3705)	(0.3101)
Pluralism	-0.4966	-0.1089	0.5165
	(0.4727)	(0.4132)	(0.4432)
Media	0.1061	0.3852	-0.5845
	(0.3897)	(0.4456)	(0.5007)
Economic liberalization	0.8572*	0.1660	-0.0844
	(0.4675)	(0.3609)	(0.3602)
Civil society	0.0862	-0.3312	0.4561
	(0.4262)	(0.4511)	(0.3313)
Political structure	0.1547	0.2135	0.0032
	(0.3975)	(0.4934)	(0.4157)
Elites	0.0622	0.3180	-0.2972
	(0.3450)	(0.3470)	(0.3791)
Corruption	-0.6461*	-0.6675*	-0.0293
	(0.3612)	(0.3636)	(0.3165)
Local self-government	-0.0692	-0.5729	-0.1465
	(0.3263)	(0.3979)	(0.3514)
Constant	2.4693**	2.4875**	0.6345
	(1.1020)	(1.0274)	(0.8160)
F-test for joint significance (p-value)	0.3740	0.4993	0.4836
R-squared	0.1438	0.1342	0.1459
Observations	78	78	78

Table A6

Quantifying omitted variables bias: Altonji ratios

The odd columns in this table replicate our baseline regressions (cf. Table 4) while the even columns also include the following locality-level controls: average distance of bank branches to their national HQs; average equity-to-assets ratio of banks (weighted by the number of branches of each bank); bank branch density; share of firms with a high-speed internet connection; share of firms that experienced a power cut in the past year; and five variables that measure the locality-level average of firms' perceptions of the following business constraints: security, business licensing, political instability, courts and education. The Heckman selection equation and the first stage of the IV estimation are not reported (first-stage statistics are presented in the last two rows). The dependent variable is *Technological innovation* in columns 1-2, *Product innovation* in columns 3-4, and *Process innovation* in columns 5-6. The Altonji ratios are measured following Altonji, Elder and Taber (2005). The ratios in the odd columns are based on a comparison of our baseline specification (shown in these columns) to an (unreported) specification without firm controls. The ratios in the even columns are based on a comparison of a specification with firm and locality-level controls (shown in the even columns) to an (unreported) specification without any such controls. The Altonji ratio equals the value of the coefficient in the regression including the controls divided by the difference between this coefficient and the one derived from the regression without the controls. All regressions include the inverse Mills' ratio, industry and district fixed effects, and a constant. Robust standard errors are clustered at the industry level and shown in parentheses; *, **, *** indicate significance at the 10%, 5% and 1% level, respectively. The F-statistic on IVs is for the F-test that the instruments are jointly insignificant, while the p-value of the Hansen J-statistic is for the overidentification test that the instruments are valid. Table A1 contains all variable definitions.

Dependent variable:	Technological innovation		Product innovation		Process innovation	
	(1)	(2)	(3)	(4)	(5)	(6)
Credit constrained (0/1)	-0.5522***	-0.4828***	-0.2199*	-0.2259**	-0.3323**	-0.2569**
	(0.1771)	(0.1400)	(0.1179)	(0.1114)	(0.1450)	(0.1219)
Altonji ratio:	15.21	-14.59	3.02	2.87	-9.12	-2.29
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Inverse Mills' ratio	Yes	Yes	Yes	Yes	Yes	Yes
Locality-specific controls	No	Yes	No	Yes	No	Yes
Observations	2,084	2,084	2,084	2,084	2,084	2,084
First-stage statistics:						
F-statistic on IVs	10.71	11.87	10.71	11.87	10.71	11.87
Hansen J-statistic (p-value)	0.58	0.34	0.22	0.58	0.01	0.04

Table A7

Lender type and firm innovation

This table reports OLS regression results on the relationship between the type of lender and firm innovation. All regressions include industry and locality fixed effects, firm controls and a constant. Robust standard errors are clustered at the industry level and shown in parentheses. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively. Table A1 in the Appendix contains all variable definitions.

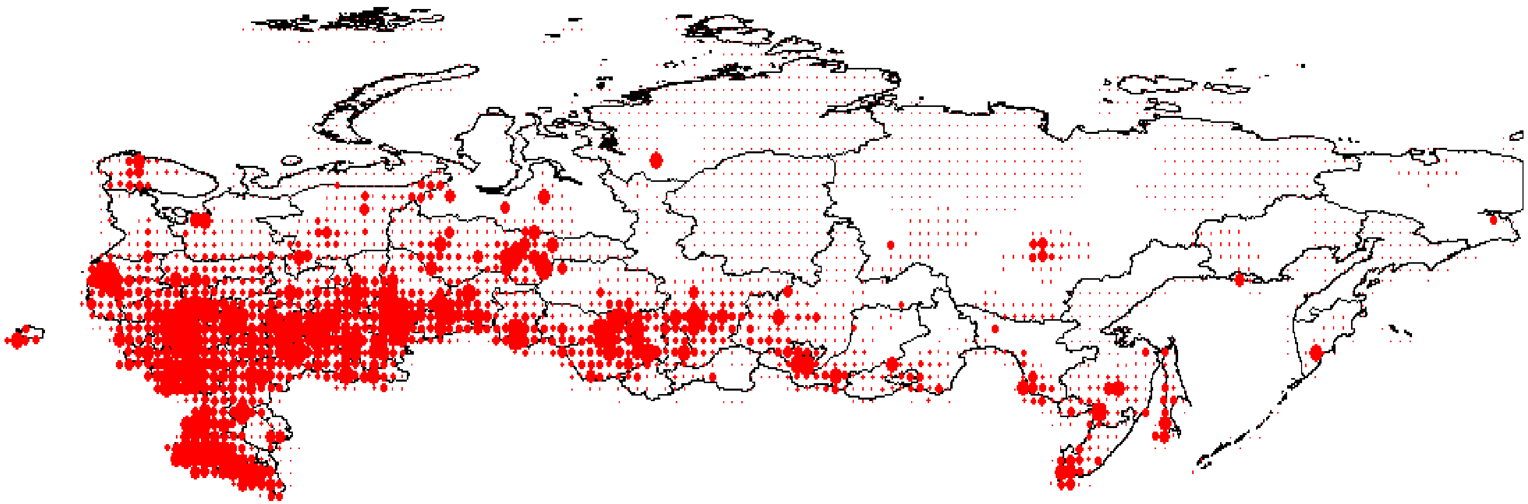
Panel A: Borrowing from a foreign bank

Dependent variable:	Technological innovation	Product innovation	Process innovation	Soft innovation	Aggregate innovation	At least 2 innovation types	At least 3 innovation types
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Foreign bank (0/1)	0.0748	0.0256	0.0492	0.1605	0.2299*	0.0916*	0.0282
	(0.0544)	(0.0353)	(0.0467)	(0.0988)	(0.1292)	(0.0484)	(0.0390)
State bank (0/1)	-0.0054	0.0256	-0.0309	0.0434	0.0366	0.0129	0.0041
	(0.0413)	(0.0233)	(0.0321)	(0.0578)	(0.0940)	(0.0419)	(0.0324)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Locality fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,026	1,026	1,026	1,017	1,017	1,026	1,026
R-squared	0.3707	0.3560	0.2813	0.2780	0.3370	0.2934	0.2774

Panel B: Borrowing from a relationship bank

Dependent variable:	Technological innovation	Product innovation	Process innovation	Soft innovation	Aggregate innovation	At least 2 innovation types	At least 3 innovation types
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Relationship bank (0/1)	0.0026	-0.0234	0.0260	0.0333	0.0493	-0.0052	0.0103
	(0.0745)	(0.0465)	(0.0495)	(0.1220)	(0.1479)	(0.0578)	(0.0401)
State bank (0/1)	-0.0525	-0.0104	-0.0421	-0.0497	-0.0916	-0.0658*	0.0039
	(0.0464)	(0.0341)	(0.0276)	(0.0824)	(0.0997)	(0.0378)	(0.0208)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Locality fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	746	746	746	739	739	746	746
R-squared	0.3956	0.3995	0.3118	0.3437	0.3756	0.3397	0.3134

(a) Economic activity across localities



(b) Bank branches across localities

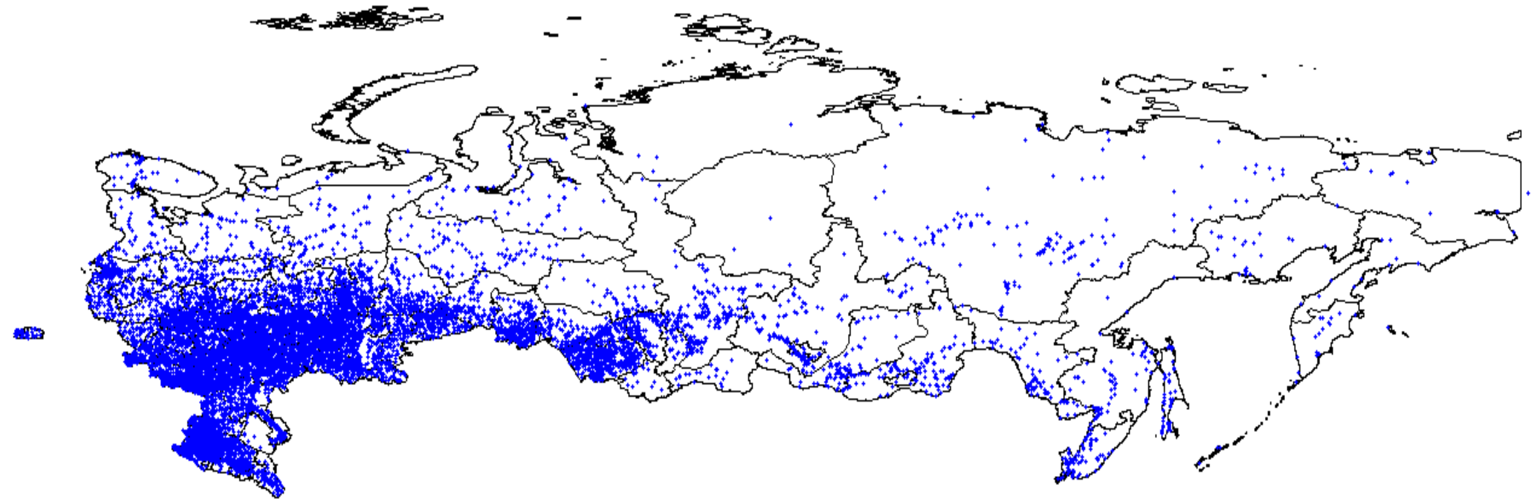


Fig. A1. These maps show the distribution of economic activity (a) and bank branches (b) across Russia. Economic activity is the (log) gross cell product (GCP) in 2005, measured in 2005 USD at PPP exchange rates. The size of each circle captures the amount of (log) GCP in the corresponding geographical cell. Data source: G-Econ project (Yale University). Bank branch data are taken from the EBRDs BEPS II survey and refer to the year 2011. Each dot indicates a bank branch.The separate western enclave is the Kaliningrad oblast.

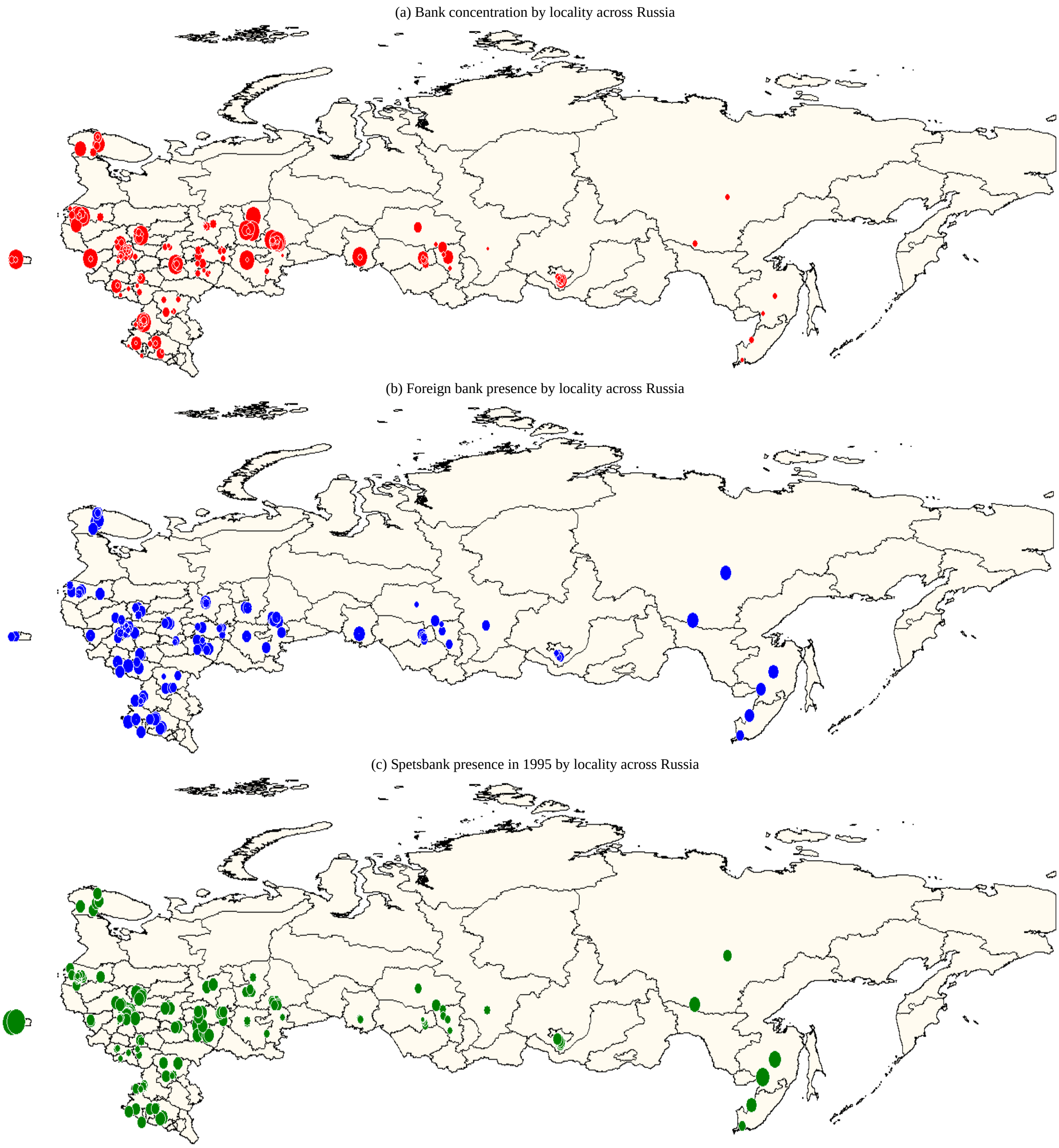


Fig. A2. This map shows the variation in (a) banking concentration (measured by HHI), (b) share of foreign bank branches, and (c) spetsbank presence (number of spetsbanks per million population) across localities covered by the BEEPS survey in Russia. Larger circles indicate higher values for the corresponding variable. The separate western enclave is the Kaliningrad oblast.

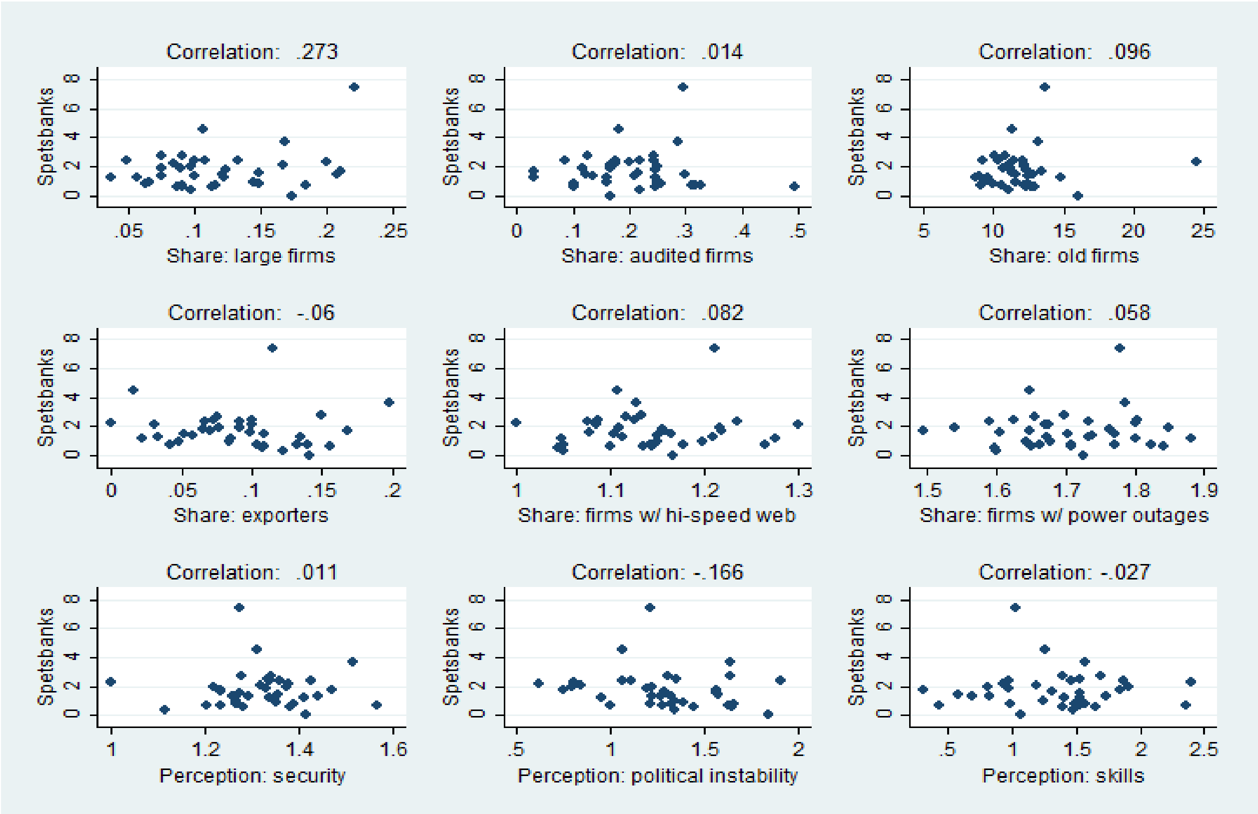


Fig. A3. This figure shows scatter plots of the number of spetsbanks per million population versus various regional firm characteristics. Regional firm characteristics are: the share of large (100+ employees) firms; share of firms that are externally audited; average firm age; share of exporter firms; share of firms with a high-speed internet connection; share of firms that experienced a power cut in the past year; and three variables that measure the regional average of firms' perceptions of the following business constraints: security, political instability, and education/skills. Source firm characteristics: EBRD-World Bank BEEPS survey.

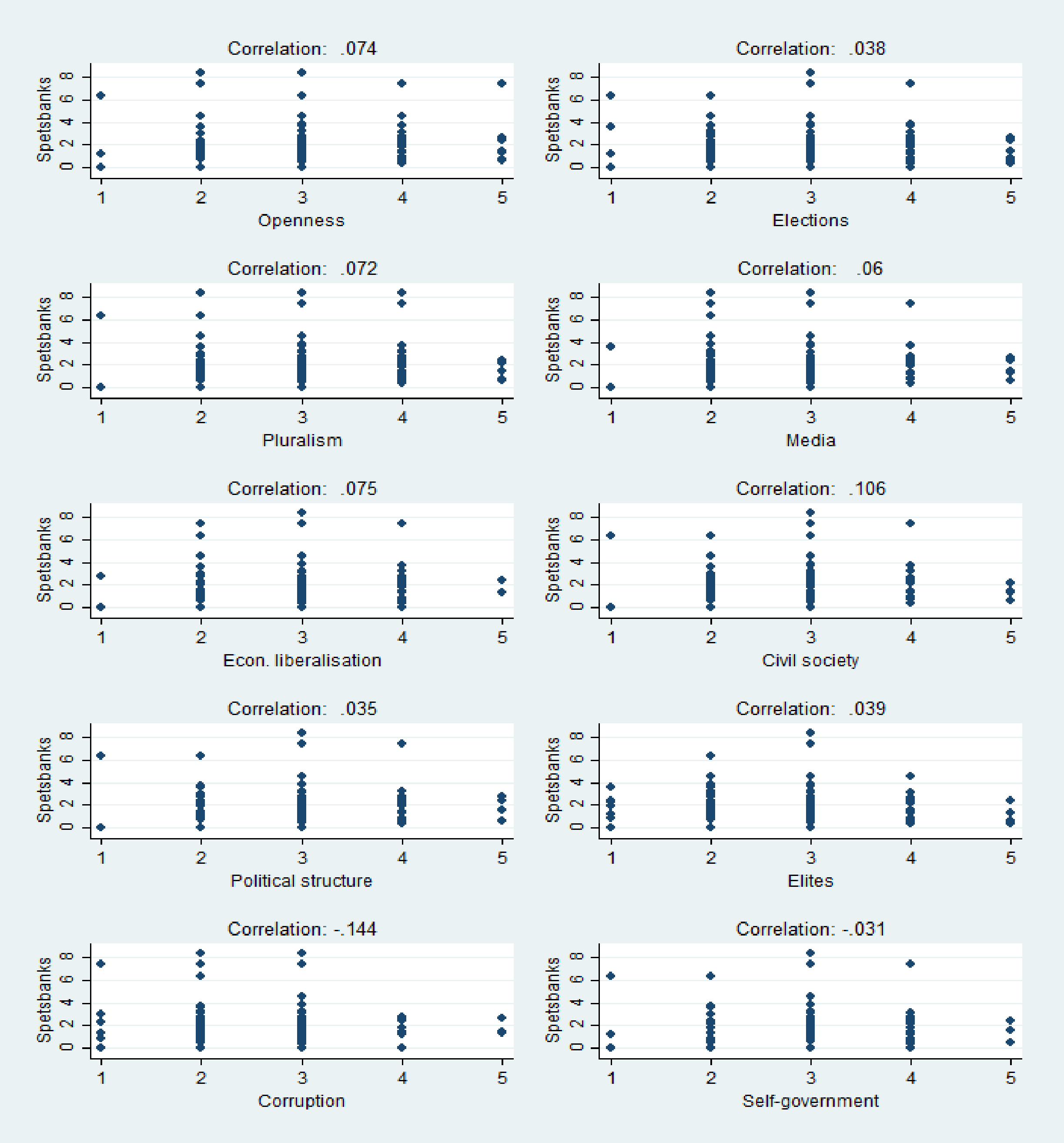


Fig. A4. This figure shows the correlations between the number of spetsbanks per million population versus various regional political and economic sub-indicators as taken from Bruno et al. (2013) who source them from Nikolay Petrov and Aleksei Titkov at the Carnegie Moscow Center (http://atlas.socpol.ru/indexes/index_democr.shtml). See Bruno et al (2013) for a detailed description of these indicators.

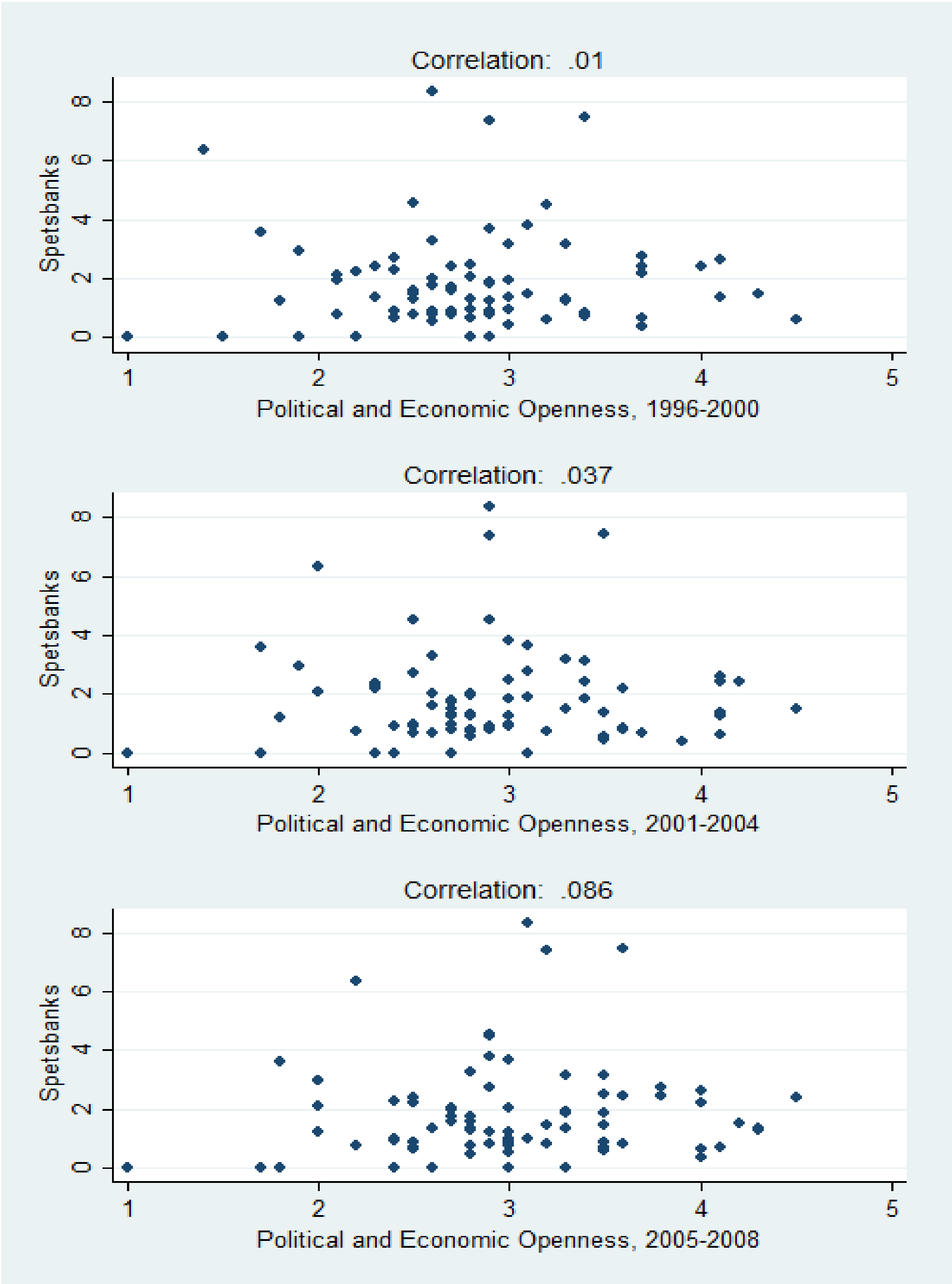


Fig. A5. This figure shows scatter plots of the correlation between the number of spetsbanks per million population and the average of regional political and economic sub-indicators from Bruno et al. (2013) for the three time windows for which these indicators were collected.

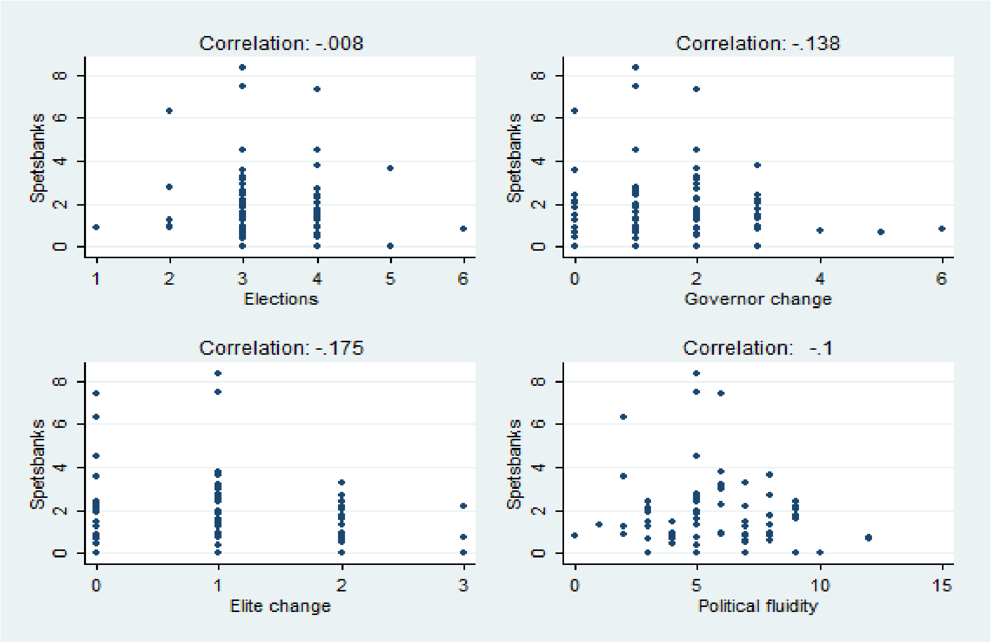


Fig. A6. This figure shows the correlations between the number of spetsbanks per million population versus the regional governor change and political fluidity variables from Bruno et al. (2013). See Bruno et al. (2013) for a detailed description of these indicators.

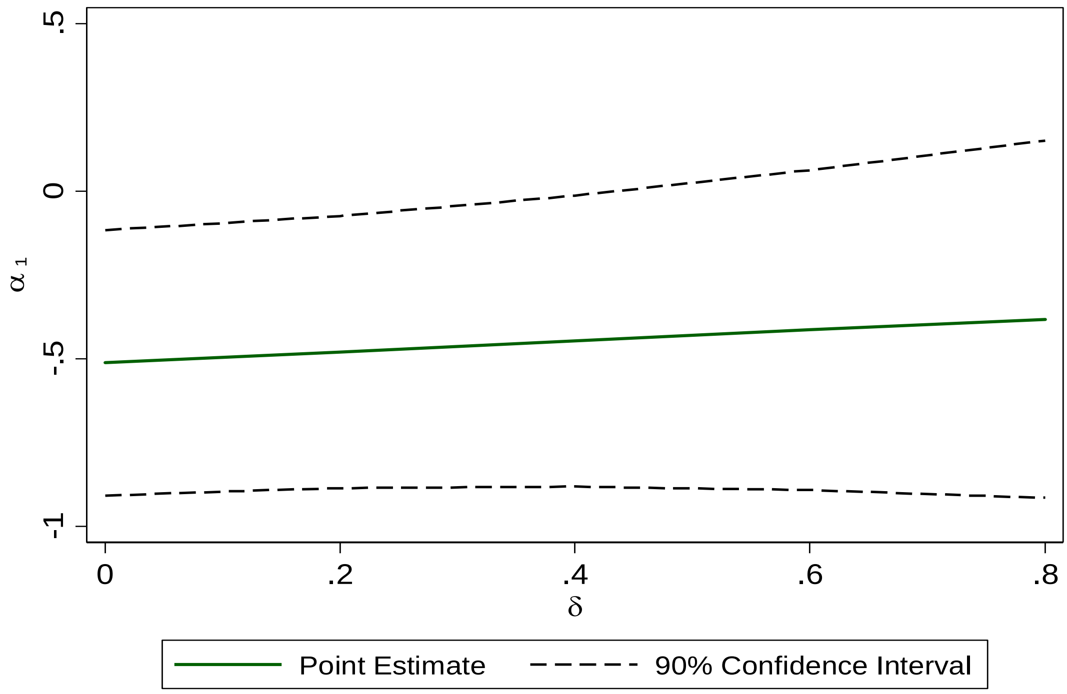


Fig. A7. This figure shows the point estimate and 90% confidence interval for the impact of credit constraints on technological innovation (α_1 in Equation 1) when the IV exclusion restriction is gradually relaxed. We follow the local-to-zero approach of Conley, Hansen and Rossi (2012) using the prior that the direct effect of local bank concentration and foreign-bank ownership on innovation is weakly positive. δ is zero corresponds to the strict exogeneity case while higher values of δ indicate a gradual weakening of the exogeneity assumption.